Dependence patterns among Banking Sectors in Asia: A Copula Approach

Jones Odei Mensah and Gamini Premaratne

Universiti Brunei Darussalam, Universiti Brunei Darussalam

October 2014

Dependence patterns among Banking Sectors in Asia: A Copula Approach

Jones Odei Mensah [a, *] and Gamini Premaratne [b,1]

[a,b] *School of Business & Economics, University of Brunei Darussalam, Gadong BE1410, Brunei*

Abstract

The bitter experience of the subprime crisis of 2007, the Global Financial crisis of 2008, and the extremely slow and painful ensuing recovery, has raised systemic risk to the center stage of global economic discourses. The crisis has brought home the urgent need for a thorough assessment of the dependence and interaction between banking sectors, from which most of the trouble began. This study investigates patterns and trends in absolute and tail dependence over time using daily returns for banking sectors from 12 Asian economies during the period 2000-2012. Static and time-varying Copula models, Gaussian copula, Symmetrized Joe-Clayton copulas, are employed to study the tail co-movements among the selected markets. The paper assumes a skew-t distribution for the innovation process of the marginal models. The results of the marginal models suggest strong volatility persistence in all twelve markets. There is high persistence in the absolute dependence of among market pairs. The evidence from the empirical analysis suggests that the cross-sectional average copula correlations generally remain at moderate levels with slight upward trend for all twelve markets. Correlation among the banking sectors of the advanced Asian markets economies are generally higher compared with the Emerging markets economies. The tail dependence is asymmetric across most of the market pairs; tail dependence at the lower side of the joint distributions is mostly higher than tail dependence at the upper side of the joint distributions. The results show that tail dependence is not upward trending for most of the pairs examined. However, the tail co-movements show significant spikes in response to financial stress in the global economy, which implies that there could be joint crashes in the regional banking system during extreme negative events. The fact that the region has not been the epicenter for most of the crisis periods covered in this study, yet responds significantly, makes it necessary for adoption of policies that maximize resilience to shocks. The study concludes that time-varying copulas are best suited for modeling the dependence structure of the Asian banking sector indices compared with static copula.

JEL Classification: C14, F36, G10

Keywords: Asia Banking Sector; DCC Correlation; Dynamic Copula; Asymmetric dependence

---

* Corresponding author. Tel.: +673 7156754
Email addresses: 11h8153@ubd.edu.bn (J.O. Mensah), gamini.premaratne@ubd.edu.bn (G. Premaratne)
[1] Tel.: +673 2463001 EXT - 11

1. Introduction and Literature Review

The bitter experience of the subprime crisis of 2007, the Global Financial crisis of 2008, and the extremely slow and painful ensuing recovery, has raised systemic risk to the center stage of global economic discourses. The crisis has brought home the urgent need for a thorough assessment of the dependence and interaction between banking sectors, from which most of the trouble began. The need to understand the relationship between different markets is of broader importance to international diversification, which seeks to minimize the risk of assets through optimal allocation. It is generally accepted that the degree of asset dependence is key to realizing the benefits from international diversification (Samuelson, 1967; Ibragimov, Jaffee, & Walden, 2009; Shin, 2009; Veldkamp and Van Nieuwerburgh, 2010; and Bai and Green, 2010) and markets with high positive dependence do not provide risk reduction benefits to investors. Moreover, international investors depend on measures of dependence and tail risk so that they can manage risks of their portfolio. Therefore, it is necessary to uncover the dependence between diverse markets.

This study investigates patterns and trends in absolute and tail dependence over time among banking sectors in Asian markets in light of recent developments in the global financial market. Assessing the comovement of Asian bank stock return is important for understanding the probability of financial shocks as well as its impact on the economies in the region. Besides, knowledge of the dependence across the banking sectors is of interest to regulators and policy makers whose duty includes ensuring a healthy and robust financial system. Apart from the size (as measured by market capitalization) and idiosyncratic risk, the interconnectedness among banking sectors is a key determinant of their systemic risk contribution or exposure. In this regard, the paper sheds light on whether there is any potential systemic risk within the Asian banking sector.

There is a grand literature on financial market dependence in both regional and inter-regional studies. The seminal contributions of Grubel (1968) on gains from international portfolio diversification served as a springboard for subsequent contributions in that line of research. Grubel (1968) pointed out that investors could obtain welfare gains by diversifying their portfolio internationally, where the gains hinges primarily on the correlation between stocks. Other early works on comovement and gains from diversification include Levy and Sarnat

(1970), Agmon (1972) and Solnik (1974) who documented that diversifying internationally could lead to greater benefits than investing locally. Subsequent works studying the comovement of international stock prices include King, Sentana and Sushil (1994), Lin, Engle and Ito (1994), Longin and Solnik (1995, 2001), Karolyi and Stulz (1996), Forbes and Rigobon (2002), Brooks and Del Negro (2005, 2006). Most of these studies present evidence that stock return comovement varies with time. For instance, Brooks and Del Negro (2004), Kizys and Pierdzioch (2009) Rua and Nunes (2009) found evidence that international comovement has been on an upward trend, particularly among developed markets.

Most of the previous studies focus on the linkages across different stock markets (see Rahman and Yung, 1994; Li, Yang, Hsia and Chang, 2005;Chiang and Jeon, 2007; Tai, 2007; Cho and Parhizgari, 2008; Kizys and Pierdzioch, 2009; Ozdemir, 2009; Khan and Park, 2009; Huyghebaert and Wang, 2010; Jayasuriya, 2011). However, there is still scope for more empirical investigations on banking sector return comovement within the region. To begin with, research in this area has focused particularly on assessing the comovement of stock returns through the correlation coefficient, which can only provide evidence on the linear association between the variables, whereas the dynamic properties have been studied through a rolling window correlation coefficient (see, for instance, Brooks and Del Negro (2004)). In cases where an attempt has been made to capture the non-linear dependence, the focus has mostly been on developed markets in Europe, North America with a few Asian markets (see Chollete, Peña and Lu, 2011; Bhatti and Nguyen, 2012; Reboredo, 2013). Moreover, the dataset employed have mostly been national or aggregate stock market indices rather than specific sectors of the financial market. Studies on that focus on the linkages across the banking sectors of Asia, which is of prime importance to the health of the financial system, are lacking. It is also rare to find studies that combine different measures of dependence. Thus, this paper sheds some light on these aspects.

Examining the dependence between markets calls for proper statistical models as applying models with a bad fit can cause suboptimal portfolios and imprecise calculation of risk exposures. The most familiar measure of dependence in finance is correlations. Researchers in the past have resorted to the Pearson correlation coefficient as a means of measuring dependence between random variables, owing to its tractability. This traditional approach shows the linear relation between two sets of data and it is computed as the covariance divided by the product of standard deviations. As to the application of the Pearson correlation to financial markets, a number of arguments have been proffered against it. For instance, it is affected when a monotonic transformation is applied to it. In other words, correlation between two return series may change if the returns are squared. Another weakness of the Pearson correlation is that the weight given to both positive and negative returns are same. In addition, large and small outcomes are not distinguished in terms of weight. Moreover, it tends to underestimate the risk from joint extreme events (Poon, Rockinger, & Tawn, 2004; and Tastan, 2006).

To avoid these drawbacks, some previous studies (Ang and Chen, 2002; Tastan, 2006; and Dungey and Martin, 2007), have relied on Multivariate-GARCH models with as an alternative to model the dependence between returns. Other studies (Ang and Bekaert, 2002; and Ang and Chen, 2002) consider Hamilton's regime-switching models as an alternative approach to model the dependence structure of returns. However, one major weakness from these previous works is the assumption that return innovations are characterized by a symmetric multivariate normal or Student-t distribution (Patton, 2006b; Garcia and Tsafack, 2011; and Wang, Wu and Lai, 2013).

Even though Multivariate GARCH models, such as the example in Longin and Solnik (1995) overcomes the drawbacks of rolling correlation, it is subject to dimensionality problems when large datasets are used (Solnik and Roulet, 2000; Christoffersen, Errunza, Jacobs, & Langlois, 2011). Due to this drawback, some studies on cross-country correlation (King, Sentana, and Wadhwani, 1994; Brooks and Del Negro, 2003; Forbes and Rigobon, 2002; Carrieri, Errunza, and Hogan, 2007; Goetzmann, Li, and Rouwenhorst, 2005; Baele and Inghelbrecht, 2009) have mostly relied on factor models, which also have the potential of bias inference (Christoffersen, Errunza, Jacobs, & Langlois, 2011).

Thus, this paper examines the dependence structure among banking sector stocks in 12 Asian economies and thereby contribute to our understanding of the cross-country dependence in a number of ways. First, the paper implements the static and dynamic Gaussian copula model and further estimates time-varying non-linear dependence between the banking sectors of 12 Asian markets. Financial returns usually exhibit fat-tails; thus, it is not enough to capture the absolute dependence but also to focus on the dependence between tail events. The paper employs both static and time-varying copula models – time-varying Gaussian, static and time-varying symmetric Joe-Clayton copula – to capture the nonlinear tail dependence structure across the banking sectors and hence foretell whether there is potential for systemic risk within the region. Copula models provide a way of capturing the dependence structure of a joint distribution, while separating the behaviour of the marginal distributions. It allows much flexibility in forming a joint distribution, which is made up of different types of marginal distributions that are able to capture nonlinear dependence between variables (Heinen & Valdesogo, 2012). It is a "pure" measure of dependence and not affected by strictly increasing transformations of data; that is, it is "scale invariant" (Nelsen 2006). In addition, it is able to capture serial dependence and asymmetric dependence, which is a common stylized fact of financial returns. By combining these econometric methods, we are able to measure the comovement between the banking sectors at various sides of the joint distributions. In analysing the dependence structure across the Asian banking sector, this paper aims to contribute to policy makers' attempts in attaining and sustaining a stable financial system.

The second contribution of the paper lies in its use of industry level data rather than aggregate equity returns. We focus on daily closing Banking sector indices for 12 Asian economies, both Developed and emerging markets over the period January 4, 2000 to December 31, 2012. Analysing comovement at industry level broadens our knowledge on the pattern of correlation across the Asian countries. This part of the of the chapter contributes to the strand of literature that examine whether differences in equity return co-movements are linked to differences in industrial structure; Griffin and Karolyi (1998), Heston and Rouwenhorst (1994) and Roll (1992).

The results of the marginal models show strong volatility persistence in all the twelve Markets. There is also high persistence in the absolute dependence of among market pairs.The evidence from the empirical analysis suggests that the cross-sectional average copula correlations generally remain at moderate levels with slight upward trend for all twelve markets. Dependence among the banking sectors of the advanced Asian markets economies are generally higher compared with the Emerging markets economies. In addition, the dependence between the Asian banking sector pairs tends to rise during financial turmoil and remains low during tranquil periods. This finding indicates the possibility of contagious shocks spreading easily across the regional banking sector.

The results, based on quantile dependence, show more dependence in the lower tail observations than in the upper tail observations for most of the market pairs. Results from dynamic SJC copula do not indicate upward trend in tail risk for most of the pairs. However, we find that tail dependence is asymmetric across the region, which suggest that investors react more towards bad news than good news in other markets.

There is also evidence that the market pairs tend to have significant lower tail dependence during extreme negative events compared with upper tail dependence; that is, asymmetric tail dependence. The dynamic path for the tail dependence shows sharp spikes in response to financial crises, suggesting that there could be joint crashes in the regional banking system during extreme negative events. Considering the fact that most of the past major financial crises – subprime crisis, and Eurozone Debt Crisis – did not begin from Asia, the broader implication of this finding is that the banking sectors across the region can face major disruptions jointly crash in response to external shocks. This makes it necessary for adoption of policies that maximize resilience to shocks.

The paper proceeds as follows. Section 2 presents a brief discussion of copula theory. Section 3 highlights the empirical application of copula models while section 4 presents the data and summary statistics of the markets under this study. Section 5 presents the empirical results on absolute and tail dependence across the markets. Section 6 concludes.

2. Copula Dependence Theory

Traditional measures of correlation as a measure of dependence are only appropriate when we assume an elliptical distribution – multivariate Gaussian or Student-t. In other words, correlation is reliable only when there is a linear relation between the returns. However, when nonlinear relationships exist between the returns, correlation could be misrepresentative (Embrechts et al, 2001; Heinen & Valdesogo, 2012), thus calling for alternative statistical tools. Since financial returns usually exhibit fat-tails, this study employs Copula models, which are known to provide a way of capturing the dependence between random variables in a more flexible way. Copula also provides a flexible way of capturing dependence at the tails of the joint distribution.

2.1. Sklar's Theorem

Sklar's theorem (Sklar, 1959) forms the basis for copula theory. Sklar (1959) showed that a joint distribution with *n*-dimension can be decomposed into its *n* marginal distributions and an *n*-dimensional copula, which fully captures the dependence between the variables. As a result, one can apply different models for the marginal distributions and later construct a valid multivariate distribution that is consistent with the marginals, thus circumventing the common assumption of normality which is mostly the case in most studies.

Define a continuous *n*-variate cumulative distribution function as $F(x_1, \dots x_n)$, whose univariate margins are $F_i(x_i)$, i=1, ...,n, where $F_i(x_i) = F(\infty, \dots, x_i, \dots, \infty)$. Given these conditions, Sklar (1959) showed that there exist a function *C*, known as a *copula*, mapping $[0,1]^n$ into [0,1] such that

$$F(x_1, \dots x_n), \; = C[F_1(x_1), \dots, F_n(x_n)]. \tag{15}$$

By differentiating the above equation once with respect to all arguments, we obtain the joint density function, which is given by the product of the copula density and the *n* marginal densities

$$\frac{\partial^2 F(x_1, \dots, x_n)}{\partial x_1, \dots, \partial x_n} = \prod_{i=1}^{n} f_i(x_i) \frac{\partial^2 C[F_1(x_1), \dots, F_n(x_n)]}{\partial F_1(x_1), \dots, \partial F_n(x_n)} \tag{16}$$

Further, if we define $u_i = F_i(x_i) \sim U[0,1]$, i=1,…,n as the probability integral transformations (PIT) variables of the marginal models, then the unconditional copula will be defined as the multivariate distribution with uniform [0,1] margins

$$C(u_i, \dots, u_n) = F\left(F_1^{-1}(u_i), \dots, F_n^{-1}(u_n)\right) \tag{17}$$

Thus, given *n* random variables, whose marginal distributions are uniform on the interval from zero to one, copulas allow an easy mapping of these univariate marginal distributions to their *n*-variate distribution, supported on $[0,1]^n$. This approach holds irrespective of the degree of dependence among the variables (Heinen & Valdesogo, 2012). A detailed review of unconditional copulas can be found in Joe (1997), Cherubini, Luciano, & Vecchiato (2004) and Nelsen (2006).

2.2. Conditional Copula

The conditional form of Sklar's theorem is due to Patton (2006b) who formulates the parameters of the marginal distribution as a time-varying process. Since the marginal distribution for returns of financial series exhibit time-varying means and volatility, the *conditional copula*, serves as a useful tool in capturing the dependence in that regard. Define the conditional copula as

$$F_t(x_{1t}, \dots, x_{nt}|\boldsymbol{Y}^{t-1}) \;= C_t[F_{1t}(x_{1t}|\boldsymbol{Y}^{t-1}), \dots, F_{nt}(x_{nt}|\boldsymbol{Y}^{t-1})] \tag{18}$$

where $\boldsymbol{Y}^{t-1}$denotes all previous multivariate process up to time $t-1$. Denoting the probability integral transformations (PIT) variables of the marginal models, as $u_i = F_i(x_i) \sim U[0,1]$, i=1,…,n , the conditional copula can be further defined as n-variate distribution

$$C_t(u_{1t}, \dots, u_{nt}|\boldsymbol{Y}^{t-1}) = F_t\left(F_{1t}^{-1}(u_{it}|\boldsymbol{Y}^{t-1}), \dots, F_{nt}^{-1}(u_{nt}|\boldsymbol{Y}^{t-1})\right) \tag{19}$$

An important step required in applying Sklar's theorem to conditional distribution is to ensure that the conditioning information be same for all marginal distributions and the copula. The common practice is to assume that the marginal models depend only on their respective past information whereas the copula can be conditioned on past information of all series.

2.3. Parameter Estimation

Estimation of the copula parameters can be carried out within two alternative frameworks. The log-likelihood function, obtained by differentiating and taking log of Eq.(18), is given by

$$L(\boldsymbol{Y}; \theta_m, \theta_c) = \sum_{t=1}^{T} log f(Y_t|\boldsymbol{Y^{t-1}}; \theta_m, \theta_c) \tag{20}$$

with θ_m denoting the parameters of the marginals and θ_c the copula parameter. Following Eq.(16), the log-likelihood function can be divided into two parts: L_m as the as the part containing the marginal densities and L_c as the part containing the dependence structure. Hence,

$$L(\boldsymbol{Y}; \theta_m, \theta_c) = L_m(\boldsymbol{Y}; \theta_m) + L_c(\boldsymbol{Y}; \theta_m, \theta_c), \tag{21}$$

$$L_m(\boldsymbol{Y}; \theta_m) = \sum_{t=}^{T} \sum_{i=1}^{n} log f_i\left(y_{i,t}|y_i^{t-1}; \theta_{m,i}\right), \tag{22}$$

$$L_c(\boldsymbol{Y};\theta_m,\theta_c)=\sum_{t=1}^{T}\log c\left(F_1\left(y_{1,t}|y_1^{t-1};\theta_{m,1}\right),\dots,F_n\left(y_{n,t}|y_n^{t-1};\theta_{m,n}\right);\boldsymbol{Y^{t-1}};\theta_c\right), \tag{23}$$

It is assumed in Eq. (22) that each variable i depends only on its own past information $y_i^{t-1}=(y_{i,1},\dots.,y_{i,t-1})$. It is important to note that the log-likelihood for the marginal models, L_m, is defined as function of the parameter vector $\theta_m=(\theta_{m,1},\dots,\theta_{m,n})$ which contains the estimated parameters of each one of the *n* marginal densities f_i. On the other hand, the log-likelihood for the copula defined directly as a function of the copula parameter θ_c, and depends indirectly on the marginal density parameters, via the distribution function F_i (Heinen & Valdesogo, 2012).

2.2.3.1 Exact Maximum Likelihood

Drawing on exact maximum likelihood procedure, the parameters of the copulas can be easily estimated. This procedure involves maximizing the joint likelihood with respect to all parameters. Hence, the maximum likelihood estimator is given as

$$\hat{\theta}_m^{ML},\hat{\theta}_c^{ML}=\text{argmax}_{\theta_m,\theta_c}L(\boldsymbol{Y};\theta_m,\theta_c) \tag{24}$$

All parameters are collected into a vector $\hat{\theta}^{ML}=(\hat{\theta}_m^{ML},\hat{\theta}_c^{ML})$. Under regularity conditions for maximum likelihood, we have

$$\sqrt{T(\hat{\theta}^{ML}-\theta_0)}\rightarrow N\left(0,F^{-1}(\theta_0)\right), \tag{25}$$

with $F(\theta_0)$ as the Fisher transformation matrix and θ_0 as the true value of the parameter. Computational difficulties arises whenever the number of parameters is very large, thus rendering the exact maximum likelihood inappropriate for large samples (Heinen & Valdesogo, 2012).

2.2.3.2 Inference for the Margins (IFM)

An alternative approach to the exact maximum likelihood is the *inference for the margins (IFM)* proposed by Joe and Xu (1996). This is a two-stage estimation procedure that is appropriate when the parameters to be estimated are large.

The first stage consists of estimating the *n* separate parameters of the marginal distributions from univariate time series, under the assumption that the marginal models are independent of each other. Hence,

$$\hat{\theta}_{m,i} = \underset{\theta_{m,i}}{\text{argmax}} \sum_{i=1}^{T} log f_i\left(y_{i,t}|y_i^{t-1};\theta_{m,i}\right). \tag{26}$$

where parameters from the first stage are collected in a vector $\hat{\theta}_m = \left(\hat{\theta}_{m,i}, \ldots, \hat{\theta}_{m,n}\right)$. Given the parameter estimated of the marginal models, the copula parameter(s) are then estimated in the second stage as

$$\hat{\theta}_c = \text{argmax}_{\theta_c} L_c(\boldsymbol{Y}; \hat{\theta}_m, \theta_c). \tag{25}$$

Under the usual regularity conditions, the following holds for the collection of the marginal and copula parameters $\hat{\theta} = \left(\hat{\theta}_m, \hat{\theta}_c\right)$

$$\sqrt{T(\hat{\theta} - \theta_0)} \rightarrow N\left(0, G^{-1}(\theta_0)\right), \tag{26}$$

where the Godambe information matrix is defined as $G(\theta_0) = D^{-1}V(G^{-1})'$ with $D = E\left[\frac{\partial_s(\theta)}{\partial(\theta)}\right]$ and $V = E[s(\theta)s(\theta)']$, where $s(\theta) = \left(\frac{\partial L_m}{\partial \theta_m}, \frac{\partial L_c(\hat{\theta}_m,\theta_c)}{\partial \theta_c}\right)$. The IFM method is the common approach used in the copula literature, although it leads to loss of efficiency compared to the exact maximum likelihood (Heinen & Valdesogo, 2012).

3. Empirical Application of Copulas

As spelled out in the previous section, copula functions allow the joining of multiple univariate distributions into a single multivariate distribution. This section explains the empirical application, that is, the fitting of appropriate marginal models and the subsequent application of the selected copula models.

3.1 Models for the Marginal Distributions

Before fitting a bivariate copula model, we must first specify a model for each of the marginal distributions. Given that financial time series exhibit some well documented characteristics such as long-memory, fat-tails, and conditional heteroskedasticity, it is appropriate that we capture these characteristics with an autoregressive (AR) and a generalized autoregressive conditional heteroskedasticity (GARCH) model. In this regard, we fit an AR(k)-GARCH(p,q) model given as follows:

$$X_{it} = \mu_i + \textstyle\sum_{i=1}^{k} \varphi_{i,k} X_{it-k} + \varepsilon_{it}, \tag{20}$$

$$\varepsilon_{it} = \sigma_{it} z_{it},\ z_{it} \sim SkT(v, \xi)$$
$$\sigma_{it}^2 = \omega_i + \sum_{i=1}^{p} \alpha_{i,p} \varepsilon_{it-p}^2 + \sum_{i=1}^{q} \beta_{i,p} \sigma_{it-p}^2 \qquad (21)$$

where X_t is the log-difference of the ith banking sector at time t, ε_{it} is the real-valued discrete time stochastic process for banking sector i at time t, with z_{it} as an unobservable random variable belonging to an i.i.d. process, σ_{it}^2 denote the conditional variance of ε_{it} where ω, α_1 and β_1 are the constant, ARCH parameter and GARCH parameter respectively. The subscripts k, p and q are the order of autoregressive terms, ARCH terms and GARCH terms, in that order. In estimating the marginal models, we assumed the skewed-*t* distribution of Hansen (1994) for z_{it}. The skewed-*t* distribution comes with two "shape parameters": the degree of freedom parameter, $v \in (2, \infty]$, which captures the tail thickness, and an skewness parameter, $\xi \in (-1,1)$, which determines the degree of asymmetry in the distribution. When $v \to \infty$ it becomes a skewed Normal distribution, when $\xi = 0$ we obtain the standard Student's t distribution, and when $v \to \infty$ and $\xi = 0$ it becomes $N(0,1)$ (Patton, 2012).

3.2. Copula Models for Bivariate Distributions

There are numerous bivariate copulas that capture the different patterns of dependence such as Gaussian, Student-*t*, Clayton, Gumbel, rotated Gumbel, Symmetrized Joe-Clayton, and a lot more. For the purpose of modelling the joint distribution of Asian banking sector indices, we apply three joint copulas: the Gaussian copula, the static Symmetrized Joe-Clayton and time-varying Joe-Clayton copulas. The subsequent subsections discuss the two copulas used in this study.

In terms of application of copula dependence, earlier studies, including Longin and Solnik (2001), Ang and Chen (2002), Hu (2006), Bhatti and Nguyen (2012) and Basher, Nechi, & Zhu (2014), have found asymmetric tail dependence in the markets they studied, which suggest a higher joint probability of downturn or upturn across the markets. Patton (2006b) also finds asymmetric dependence between the Deutschemark and the yen. Jondeau et al. (2007), Peng and Ng (2012) finds evidence of financial contagion and asymmetric tail dependence coefficient between the major international stock markets. Recently, Reboredo (2013) finds evidence of symmetric tail dependence between gold and USD exchange rates. Delatte and Lopez (2013) also document that “the dependence between commodity and stock markets is time-varying, symmetrical and occurs most of the time”.

3.2.1. Gaussian Copula

Let u and v as the cumulative density functions of the standardized residuals from the marginal models. We define the dependence structure between the margins by the following copula function:

$$C(u,v) = \int_{-\infty}^{\Phi-1(u)} \int_{-\infty}^{\Phi-1(v)} \frac{1}{2\pi\sqrt{1-\rho^2}} exp\left\{-\frac{x^2-2\rho xy+y^2}{2(1-\rho^2)} dx.dy\right\} \quad (22)$$

$$= \Phi_\rho(\Phi^{-1}(u), \Phi^{-1}(v)), -1 \le \rho \le 1 \quad (23)$$

where Φ denotes the univariate cumulative distribution of the standard normal; Φ_ρ denote the bivariate cumulative distribution of the standard normal; and ρ is the correlation coefficient between the two random variables. Earlier works on the time-varying copula models include Patton (2004), Patton (2006a), Patton (2006b), and Jondeau and Rockinger (2006). The usual specification of time-varying copula models is to come up with a dynamic equation for the dependence parameter while maintaining a fixed structure for the functional form of the copula (Bhatti & Nguyen, 2012). Here, the difficulty arises when specifying a “forcing variable” for the evolution equation of the dependence parameter (Heinen & Valdesogo, 2012). The dynamic evolution of the Gaussian copula parameters is modelled in line with the form defined in Patton (2006b) as follows:

$$\rho_t = \Lambda\left(\omega + \beta.\rho_{t-1} + \alpha.\frac{1}{10}\sum_{j=1}^{10}[\Phi^{-1}(u_{t-j}).\Phi^{-1}(v_{t-j})]\right) \quad (24)$$

Where $\Lambda = 1 - e^{-x}/1 + e^{-x}$ denote the normalized form of the inverse Fisher transformation (modified logistic transformation), which forces the ρ_t within the interval (-1,1); u_t and v_t are the probability integral transformations (PIT) of the marginal.

3.2.2. Symmetrised Joe-Clayton Copula

The symmetrized Joe-Clayton copula is a modified version of the “BB7” copula of Joe (1997) (Patton, 2006b). The model is built as a Laplace transformation of the Joe-Clayton copula which is given by

$$C_{JC}(u,v|\tau^U,\tau^L) = 1 - \left\{1 - \left([1-(1-u)^k]^{-\gamma} + [1-(v)^k]^{-\gamma} - 1^{-1/\gamma}\right)\right\}^{1/k} \qquad (25)$$

where $k = 1/\log_2(2-\tau^U)$, $\gamma = -1/\log_2(\tau^L)$, and $\tau^U \in (0,1)$, $\tau^L \in (0,1)$

The Joe-Clayton copula has the unique feature of capturing both upper tail (τ^U) and lower tail (τ^L) tail dependence. The upper tail dependence is expressed as follows

$$\tau^U = \lim_{\varepsilon\to 1} Pr[U > \varepsilon | V > \varepsilon] = \lim_{\varepsilon\to 1} Pr[V > \varepsilon | U > \varepsilon] = \lim_{\varepsilon\to 1} \frac{(1 - 2\varepsilon + C(\varepsilon,\varepsilon))}{1-\varepsilon} \qquad (26)$$

If the above limit exists, then the copula C shows upper tail dependence if $\tau^U \in (0,1]$ and no upper tail dependence if $\tau^U = 0$. Likewise, the lower tail dependence is expressed as

$$\tau^L = \lim_{\varepsilon\to 0} Pr[U \leq \varepsilon | V \leq \varepsilon] = \lim_{\varepsilon\to 0} Pr[V \leq \varepsilon | U \leq \varepsilon] = \lim_{\varepsilon\to 0} \frac{C(\varepsilon,\varepsilon)}{\varepsilon} \qquad (27)$$

If the above limit exists, then the copula C shows lower tail dependence if $\tau^L \in (0,1]$ and no lower tail dependence if $\tau^L = 0$.

Although the Joe-Clayton copula captures dependence in the upper and lower tails of the distribution, its functional form imposes some degree of asymmetry even when the two tail dependence are same. Due to this drawback, Patton (2006b) proposed the "symmetrized" Joe-Clayton, which is allows the tail dependence measures to "determine the presence or absence of asymmetry". The SJC is defined as follows

$$C_{SJC}(u,v|\tau^U,\tau^L) = 0.5.\left[C_{JC}(u,v|\tau^U,\tau^L) + C_{JC}(1-u,1-v|\tau^L,\tau^U) + u + v - 1\right] \qquad (28)$$

The SJC becomes symmetric only when $\tau^U = \tau^L$. However, its specification does not force symmetric dependence on the variables.

The time evolution for the upper and lower tail dependence parameters, as defined in Patton (2006b), is expressed as follows

$$\tau_t^U = \Lambda\left(\omega U + \beta_U.\tau_{t-1}^U + \alpha_U.\frac{1}{10}\sum_{j=1}^{10} |u_{t-j} - v_{t-j}|\right) \qquad (29)$$

$$\tau_t^U = \Lambda\left(\omega L + \beta_L.\tau_{t-1}^L + \alpha_L.\frac{1}{10}\sum_{j=1}^{10}|u_{t-j} - v_{t-j}|\right) \qquad (30)$$

where $\Lambda = (1 + e^{-x})^{-1}$ is the logistic transformation which keeps the parameters (τ^U, τ^L) within the interval of (0,1). The time varying parameter is the upper and lower tail dependence for the joint distribution.

The evolution of τ_t^U and τ_t^L is defined like a restricted ARMA (1,10) process where the autoregressive terms , $\beta_U.\tau_{t-1}^U$ and $\beta_L.\tau_{t-1}^L$ captures persistence while a forcing variables, $\alpha_U.\frac{1}{10}\sum_{j=1}^{10}|u_{t-j} - v_{t-j}|$, captures variation in the dependence. The forcing variable – defined as the absolute difference between u_t and v_t over the previous 10 observation – has an inverse relationship with the dependence, since it is zero under a perfect positive dependence, equals 1/3 under independence, and 1/2 under perfect negative dependence Patton (2006b).

3.2.3. Selecting the Best Model

It is crucial that we select the most adequate model after estimating various competing copula models. Several criteria have been proposed in the literature for this purpose; see for instance, Fermanian (2005), Chen and Fan (2005), Genest et al. (2006), Hans (2007), Berg (2009) and Bhatti et al. (2006). The most common test used for this purpose is the Akaike Information Criterion (AIC), which is defined as: $AIC = -2\log(likelihood) + 2k$,where *k* is the number of parameters in the model.

Alternatively, the Bayesian Information Criterion (BIC) can be used to select the optimal copula. It is defined as $BIC = -2\log(likelihood) + k.\log(n)$, where *n* is the number of observation and *k* is as defined earlier. The optimal copula is the one with the lowest AIC or BIC.

4. Data and Summary Statistics

The data set employed for this study consist of daily closing Banking sector indices for 12 Asian economies, both Developed and Emerging markets as follows: Hong Kong, Japan, Singapore, South Korea, Taiwan, China, Malaysia, India, Philippines, Indonesia, Thailand and Sri Lanka[1].

[1] Developed markets (DMs) include Hong Kong, Singapore, Japan & South-Korea whereas the Emerging markets (EMs) include China, Philippines, Malaysia, India, Taiwan, Indonesia, Thailand, Sri Lanka

The data is collected from DataStream and comprise of 3390 daily observations from January 4, 2000 to December 31, 2012. Figure 1 shows the price level of the Banking Sector Indices over the period January 2000 to December 2012, normalized to 100 at the start of the sample period. Figure 2 shows the daily log returns on the various indices, which indicates that all the markets exhibit large volatilities between 2007 and 2009 during which the global financial crisis hit the world's financial markets. Figure 2 also shows that all the markets exhibit volatility clustering, which is confirmed by the ARCH-LM test in table 1. The similarity in the return volatilities indicates how the markets respond to a common shock.

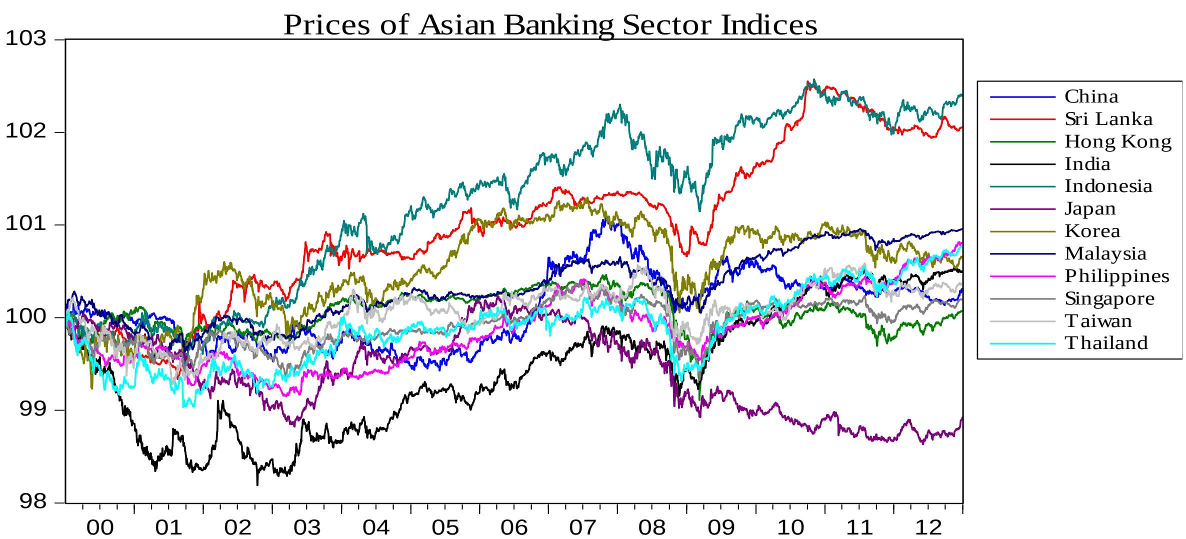

Figure 1: *The Figure shows the price level of the Banking Sector Indices over the period January 2000 to December 2012, normalized to 100 at the start of the sample period.*

Log Returns of Asian Banking Sector Indices

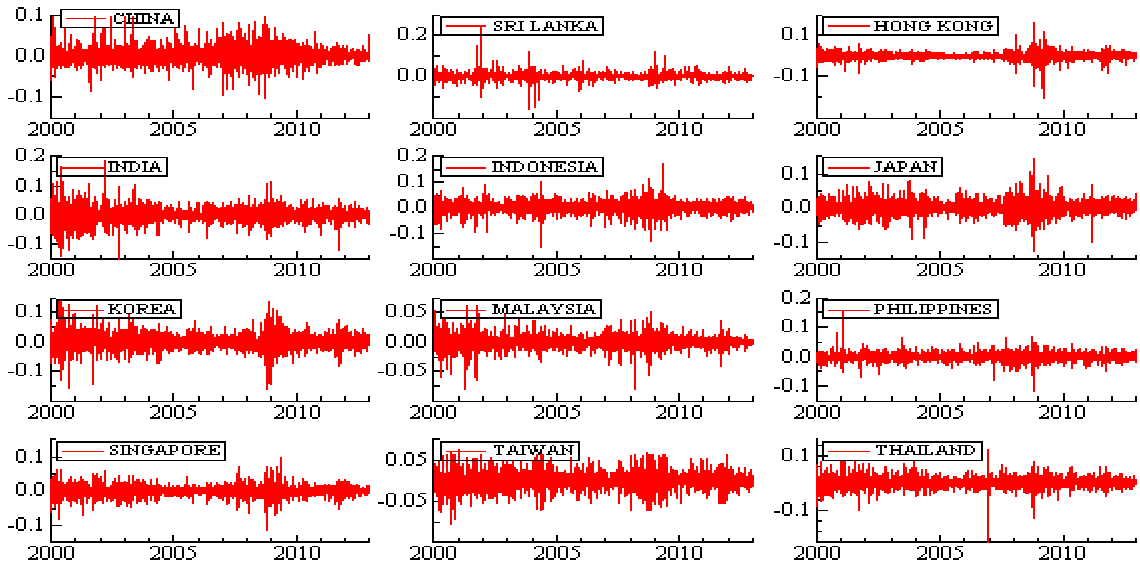

Figure 2: *The lower panel shows the daily log returns of the Banking Sector Indices over the period January 2000 to December 2012.*

Table 1 shows the summary statistics of the banking sector returns for the twelve markets. With the exception of Japan, all the markets show positive expected returns with India having the highest (0.07%) followed by Sri Lanka (0.06%), and Malaysia (0.03%). In terms of volatility (standard deviation), the Korean-banking sector ranks higher with (2.44%) while Malaysian-banking sector emerges with the lowest risk (1.04%). The markets generally do not follow the standard risk-return trade-off where high standard deviation is expected to be accompanied by high returns. For instance, Malaysia has the lowest standard deviation although it ranks third in terms of returns whereas Korea has the highest standard deviation although it ranks fourth in terms of returns.

The fourth and fifth columns of the table present the skewness and kurtosis coefficients for the markets. The skewness and kurtosis have important implications for risk management, asset allocation, option pricing and other financial market activities. Investors generally prefer stocks with low negative skewness and low kurtosis (Kim and White 2004). The markets with negative skewness include Hong Kong, India, Malaysia, Singapore and Thailand; the remaining markets have positive skewness. Reasons for high negative skewness include relatively high turnover and uncommon high returns over previous periods. The degree of skewness is also related to stock capitalization (Hashmi and Tay, 2012). The kurtosis coefficients provide evidence of fat-tail in the return distributions. In view of the presence of kurtosis in stock returns, Bollerslev (1987) proposed the *t*-distribution for the conditional distribution of standard residuals of returns to capture the conditional leptokurtosis. The skewed-*t* of Hansen (1994) also takes care of the asymmetry in the conditional distribution. Both the *t* and skewed-*t* are later employed in the GARCH modelling in the subsequent sections. The Jarque-Bera statistic strongly rejects the null hypothesis of normality in the return distributions. Finally, the ARCH-LM test of order 10 strongly confirms the presence of ARCH-effects in the individual series, which makes it valid to employ GARCH models for the conditional variance of the returns.

Table 2 shows the correlation coefficients for all the market pairs. The correlation ranges as follows: -0.0057 – 0.5114 for Pearson correlations, shown in panel A; 0.0007 – 0.3388 for Kendall's tau, as shown in panel B; and 0.001– 0.4737 for spearman's correlation, shown in panel C. On the average, the Pearson correlation is higher compared with the Kendall's tau and Spearman's measure. This observation could possibly be as a result of outliers in the returns, as buttressed by the high kurtosis shown in table 1. In general, the dependence between the banking sectors is not at high levels, as observed by the relatively low correlation coefficients.

Table 1 Summary statistics of log returns of Banking Sector Indices

	Mean	Std.Dev.	Skewness	Kurtosis	Jarque-Bera	ARCH-LM (10 Lags)	Obs
China	0.0001	0.0178	0.3243	7.6014	3050.1450***	16.8604	3390
Sri Lanka	0.0006	0.0155	1.1326	36.8655	162720.3000***	15.0053	3390
Hong Kong	0.0000	0.0154	-0.8687	27.4858	85113.5800***	79.8774	3390
Indonesia	0.0001	0.0235	0.2182	9.1720	5407.5600***	40.2053	3390
India	0.0007	0.0208	-0.1555	8.0089	3557.5560***	42.6971	3390
Japan	-0.0003	0.0189	0.0892	7.5209	2891.4150***	66.2720	3390
Korea	0.0002	0.0244	0.0727	8.8949	4911.3690***	53.9004	3390
Malaysia	0.0003	0.0104	-0.3253	9.4672	5967.5420***	35.5439	3390
Philippines	0.0002	0.0129	0.2312	13.3744	15232.6400***	9.3816	3390
Singapore	0.0001	0.0149	-0.0144	7.4463	2792.6270***	62.7885	3390
Taiwan	0.0001	0.0197	0.0407	5.0605	600.6608***	31.1757	3390
Thailand	0.0002	0.0192	-0.3215	11.1037	9334.1660***	29.9480	3390

Note: The table reports the summary statistics for the log returns of the 12 Asian Banking indices at daily frequency from January 2000 to December 2012.

Table 2 Correlation coefficients for Banking Sectors

	China	Sri Lanka	Hong Kong	Indonesia	India	Japan	Korea	Malaysia	Philippines	Singapore	Taiwan
Panel A: Pearson Correlation											
Sri Lanka	-0.0057										
Hong Kong	0.2243	0.0452									
Indonesia	0.1172	0.0085	0.2458								
India	0.1588	0.0301	0.3138	0.2029							
Japan	0.1599	0.0220	0.3866	0.2189	0.1886						
Korea	0.1666	0.0319	0.4052	0.1985	0.2389	0.3361					
Malaysia	0.1369	0.0470	0.3018	0.2123	0.2064	0.2329	0.2375				
Philippines	0.1182	0.0523	0.2785	0.2286	0.1673	0.2563	0.2160	0.2632			
Singapore	0.1796	0.0519	0.5114	0.2629	0.3436	0.3265	0.3972	0.3489	0.2364		
Taiwan	0.1337	0.0424	0.3313	0.1901	0.1975	0.2520	0.3321	0.2373	0.2191	0.2973	
Thailand	0.1455	0.0525	0.3615	0.2176	0.2683	0.2444	0.2707	0.2961	0.2263	0.3766	0.2471
Panel B: Kendall's tau											
Sri Lanka	0.0007										
Hong Kong	0.1399	0.0517									
Indonesia	0.0756	0.0178	0.1884								
India	0.0957	0.0288	0.1919	0.1352							
Japan	0.0866	0.0361	0.2371	0.1414	0.1015						
Korea	0.1127	0.0310	0.2874	0.1557	0.1461	0.2395					
Malaysia	0.0880	0.0266	0.2158	0.1515	0.1239	0.1399	0.1658				
Philippines	0.0694	0.0364	0.1558	0.1504	0.0882	0.1395	0.1342	0.1586			
Singapore	0.1201	0.0317	0.3388	0.1918	0.2072	0.1898	0.2443	0.2128	0.1335		
Taiwan	0.0895	0.0291	0.2243	0.1287	0.1178	0.1619	0.2145	0.1629	0.1417	0.1960	
Thailand	0.0970	0.0449	0.2522	0.1631	0.1701	0.1503	0.1956	0.1726	0.1363	0.2358	0.1743
Panel C: Spearman rank-order											
Sri Lanka	0.0010										
Hong Kong	0.2057	0.0765									
Indonesia	0.1113	0.0261	0.2704								
India	0.1402	0.0422	0.2789	0.1961							
Japan	0.1275	0.0528	0.3426	0.2061	0.1492						
Korea	0.1658	0.0461	0.4102	0.2249	0.2139	0.3457					
Malaysia	0.1288	0.0403	0.3116	0.2161	0.1820	0.2039	0.2401				
Philippines	0.1012	0.0547	0.2286	0.2205	0.1306	0.2046	0.1982	0.2322			
Singapore	0.1761	0.0470	0.4737	0.2739	0.3002	0.2741	0.3493	0.3045	0.1957		
Taiwan	0.1325	0.0434	0.3230	0.1860	0.1728	0.2350	0.3079	0.2362	0.2084	0.2820	
Thailand	0.1423	0.0666	0.3633	0.2339	0.2485	0.2189	0.2841	0.2487	0.2009	0.3394	0.2526

Note: The table presents the estimated correlations between the Asian banking sector indices over the period January 2000 to December 2012. Panel A presents the Pearson Correlation; panel B presents the Kengall's tau; and panel C presents the Spearman rank correlations.

The quantile dependence plots, for $q \in [0.025, 0.975]$, are presented in the left panel of Figure 3, whereas the difference between the upper and lower parts are shown in the right panel of Figure 3 [2].The red dashes represent the corresponding 90% pointwise *iid* boostrap confidence bands. The confidence bands constricts for values of q close to 0.5 (centre of the distribution) and widens when q is close to 0 or 1 (tails of the distribution). Estimating for all the pairs will result in 66 individual pairs, which is infeasible to present here due to space availability so, we present for just some selected pairs.

The right panel of Figure 3 indicates that the quantile dependence at the upper tail is relatively higher compared with the dependence at the lower tail for a few pairs such as: China-Hong Kong, China-Japan, China-Korea, and China-Singapore but the difference between the upper and lower quantile dependence probabilities is below 0.1. However, for majority of the pairs, there is more dependence in the lower tail observations than in the upper tail observations. For instance, the difference between the quantile dependence probabilities is above 0.1 for the following pairs: Hong Kong-India, Hong Kong- Indonesia, Hong Kong-Japan, Hong Kong-Korea, Hong Kong-Singapore, and Hong Kong-Taiwan.

[2] Estimation was carried out with the MATLAB Code provided by Patton

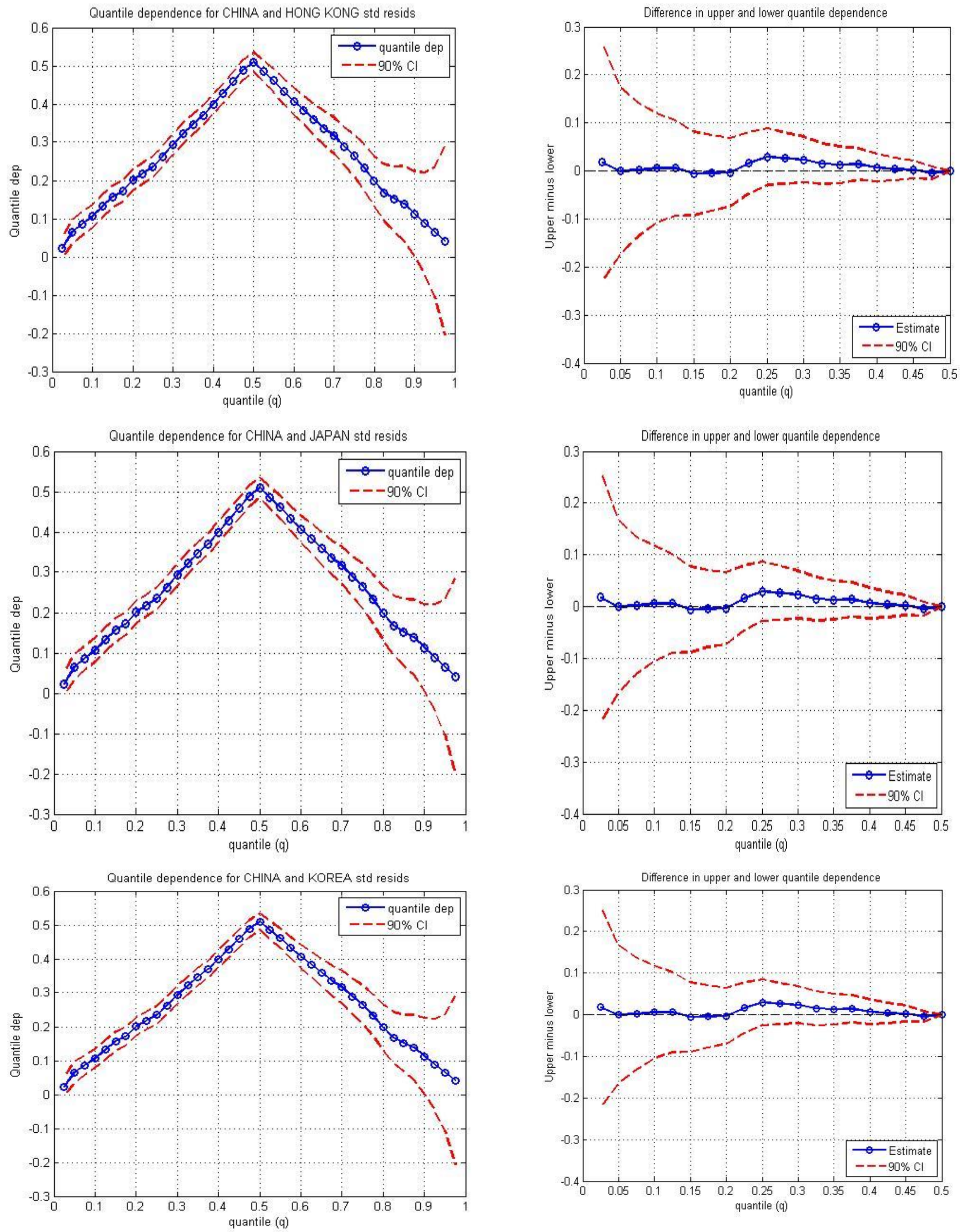

Figure 3a: *The left panel presents the estimated quantile dependence between the standardized residuals for the banking sector indices, along with 90% iid bootstrap confidence intervals. The right panel shows the difference between the upper and lower tail quantile dependence, along with a 90% iid boostrap confidence interval.*

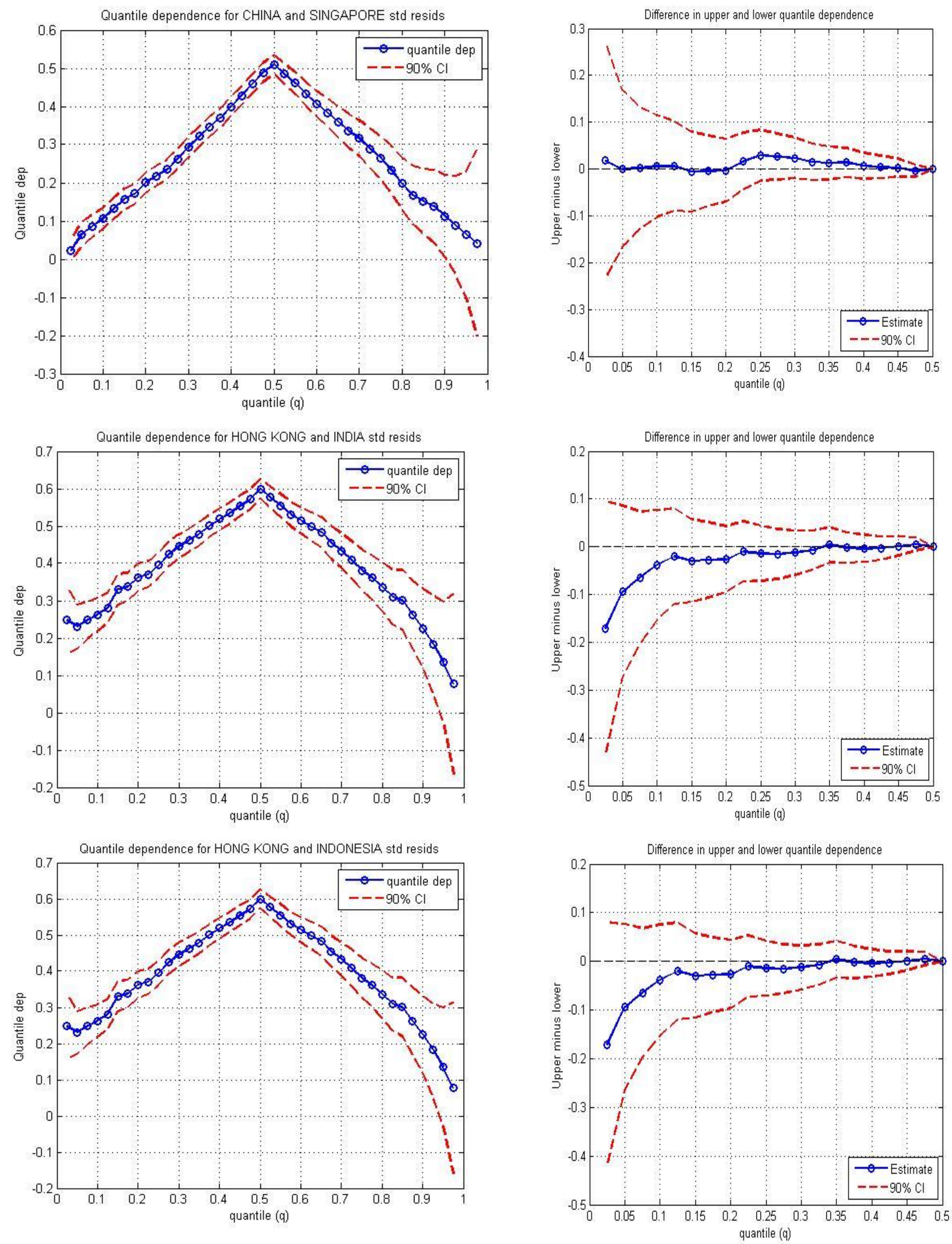

Figure 3b: *The left panel presents the estimated quantile dependence between the standardized residuals for the banking sector indices, along with 90% iid bootstrap confidence intervals. The right panel shows the difference between the upper and lower tail quantile dependence, along with a 90% iid boostrap confidence interval.*

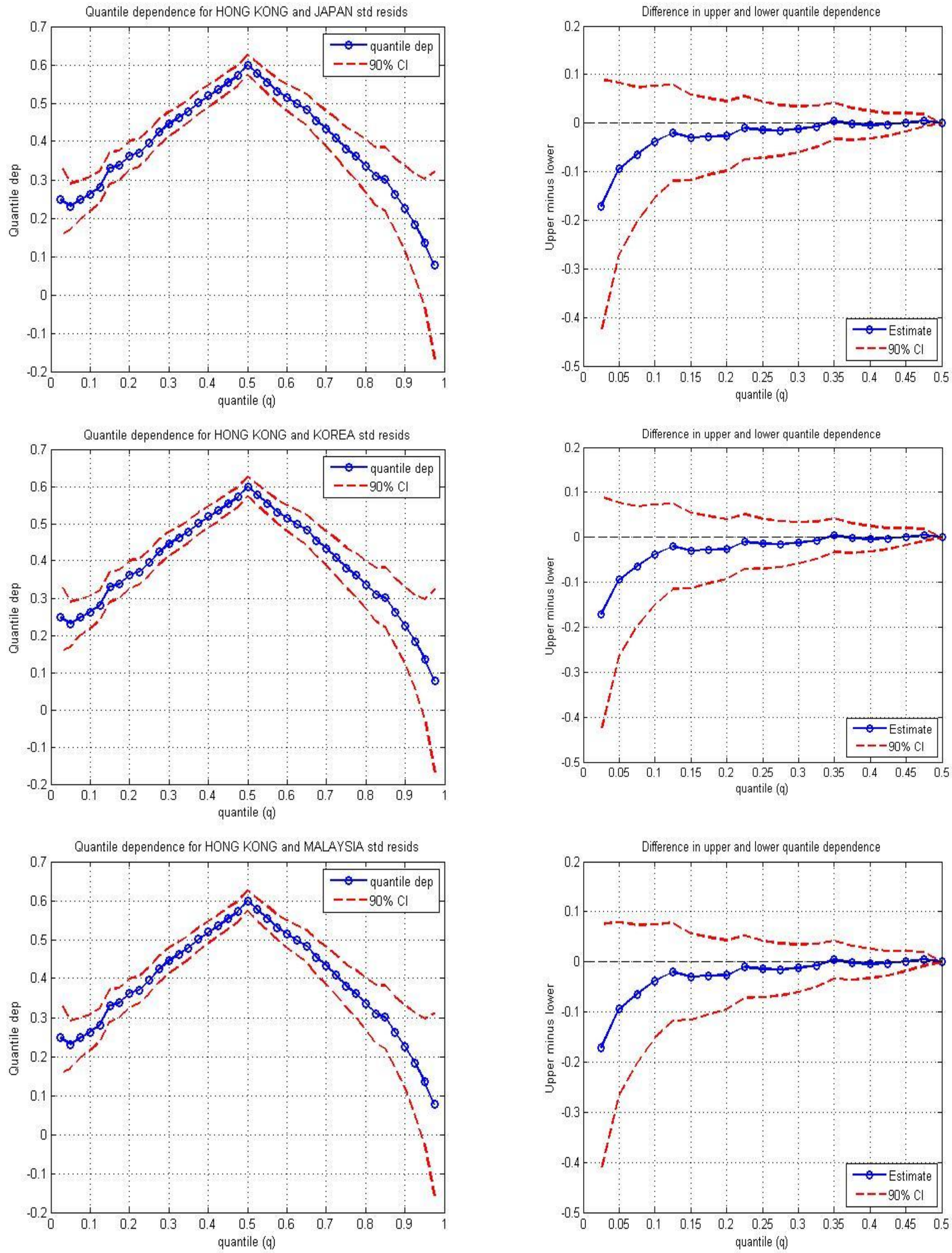

Figure 3c: *The left panel presents the estimated quantile dependence between the standardized residuals for the banking sector indices, along with 90% iid bootstrap confidence intervals. The right panel shows the difference between the upper and lower tail quantile dependence, along with a 90% iid boostrap confidence interval.*

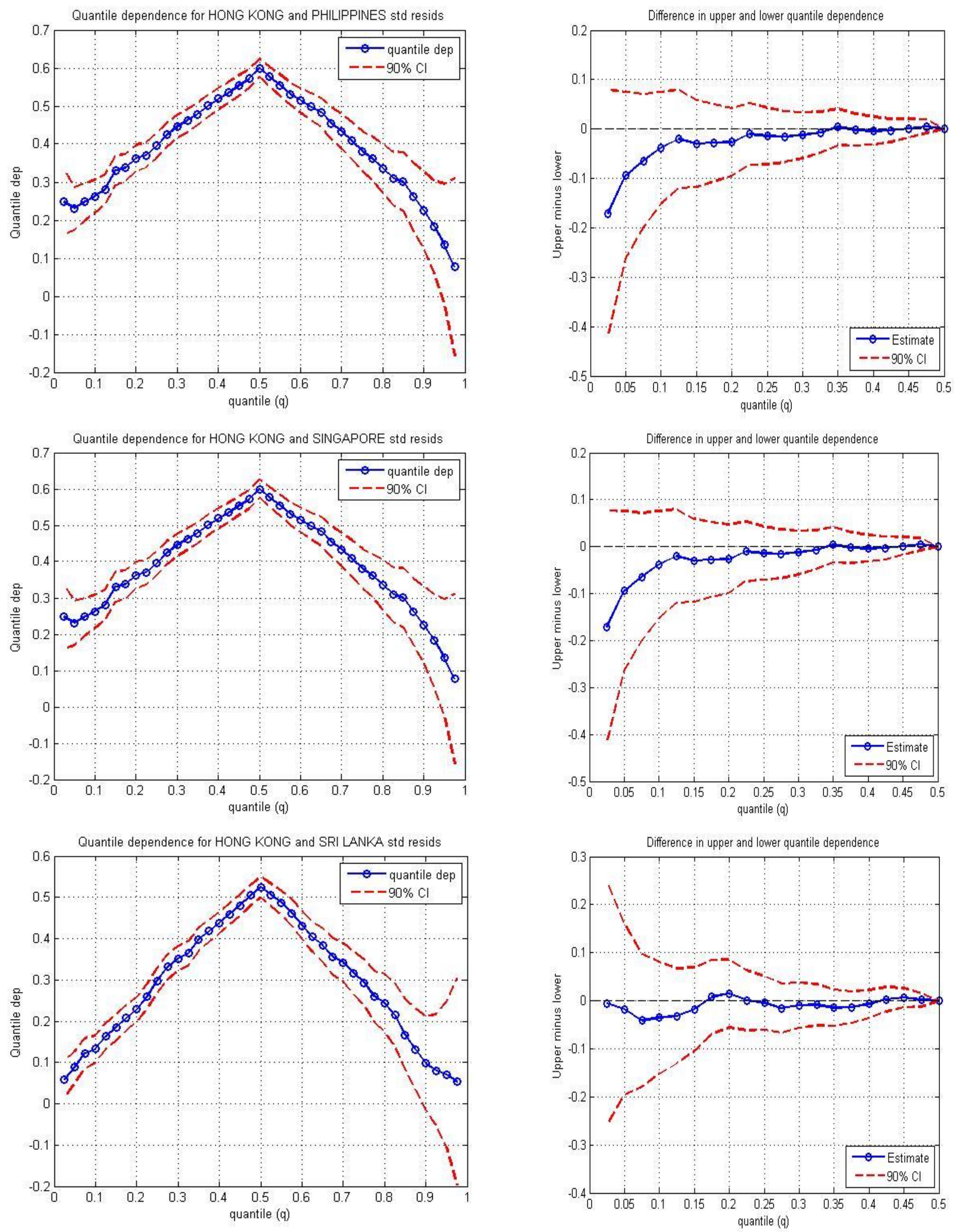

Figure 3d: *The left panel presents the estimated quantile dependence between the standardized residuals for the banking sector indices, along with 90% iid bootstrap confidence intervals. The right panel shows the difference between the upper and lower tail quantile dependence, along with a 90% iid boostrap confidence interval.*

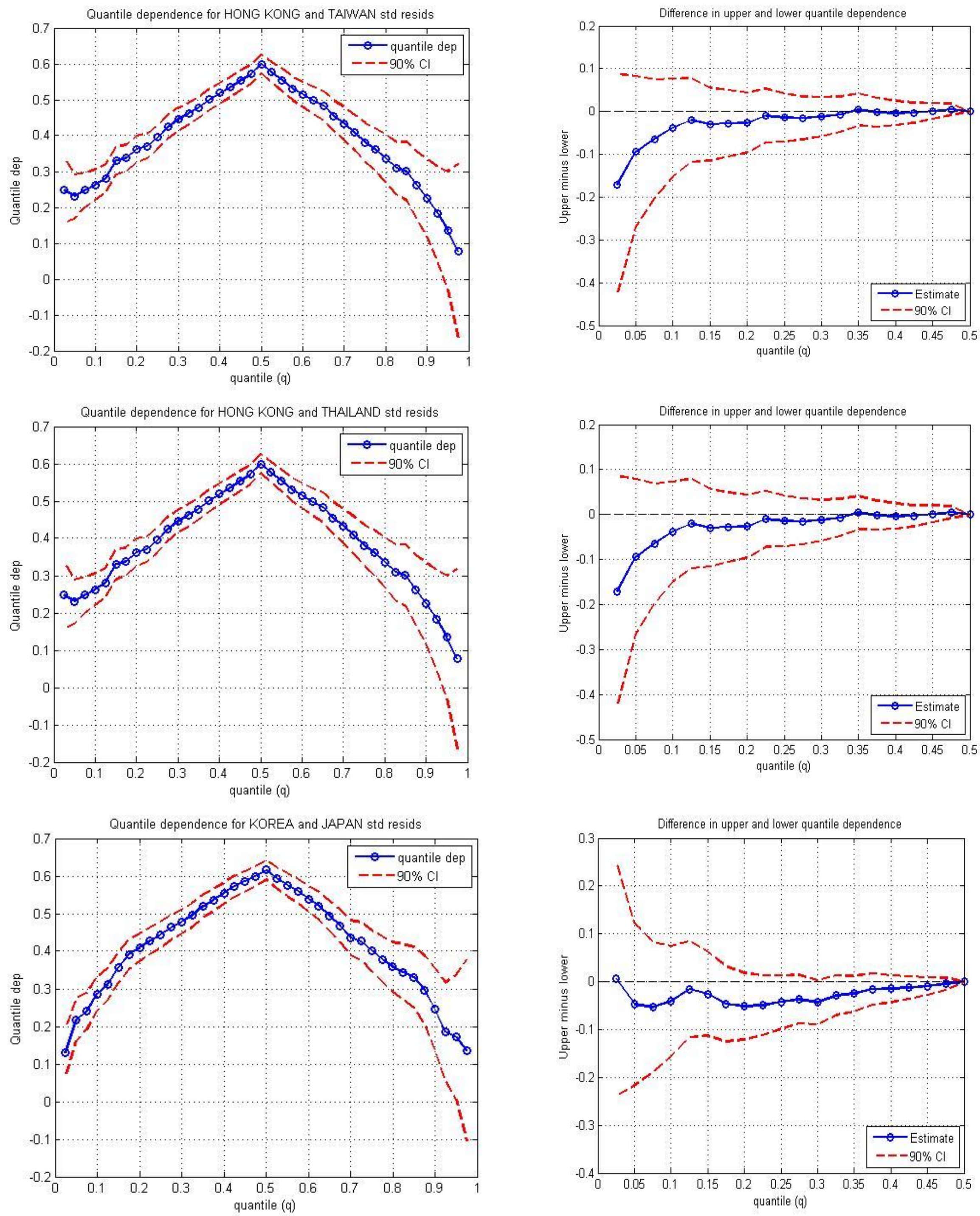

Figure 3e: *The left panel presents the estimated quantile dependence between the standardized residuals for the banking sector indices, along with 90% iid bootstrap confidence intervals. The right panel shows the difference between the upper and lower tail quantile dependence, along with a 90% iid boostrap confidence interval.*

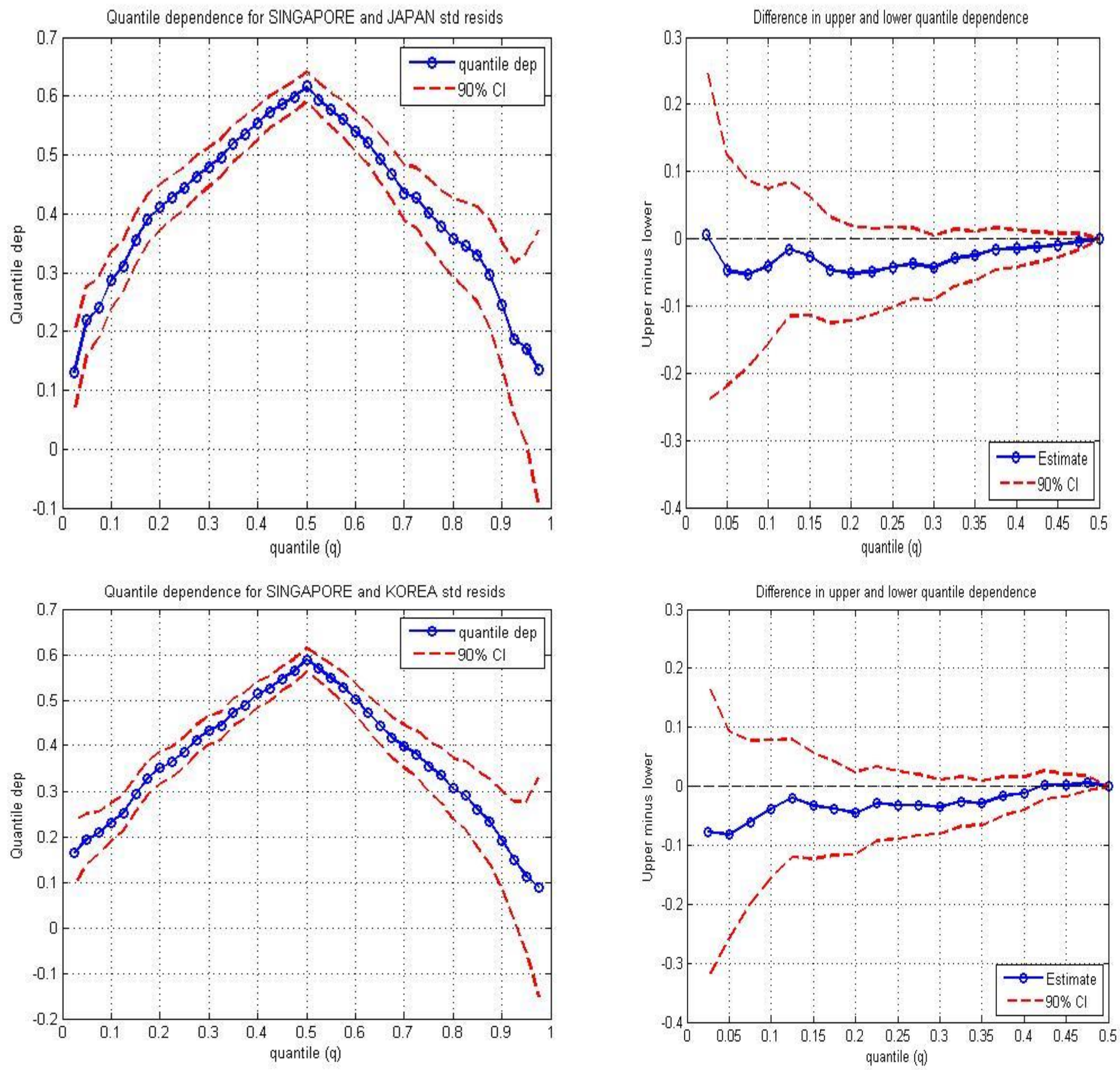

Figure 3f: *The left panel presents the estimated quantile dependence between the standardized residuals for the banking sector indices, along with 90% iid bootstrap confidence intervals. The right panel shows the difference between the upper and lower tail quantile dependence, along with a 90% iid boostrap confidence interval.*

5. Empirical Analysis and Results

The econometric analysis in this chapter relies on copula models to explore the bivariate tail dependence across the various markets, both in static and time-varying terms. A total of three copulas – one eliptical copula namely, time-varying Gaussian copula and two Archimedian copulas, symetrised Joe Clayton (SJC) and time-varying symmetrised Joe Clayton copulas. The selected copulas are chosen to represent various portfolio shapes considered in the finance literature – thin tails represented by the gaussian copula; heavy tails and asymmetric tails as captured by the SJC. The results are discussed in the ensuing sub-sections.

5.1. Results for the Marginal Models

Before proceeding to the DCC estimation, we have to specific appropriate models for the conditional means and variances of the respective series. In line with this, each of the banking sector return series was fitted with an AR-model for the mean equation. The residuals from this model have an expected return of zero, and free of autocorrelation, which is required for the further estimations. We assume that the residuals are free of common factors but rather contain only the bank specific factors and as a result, we can confidently associate changes in the conditional correlation with changes in the cross-country risk of the banking sector (Schröder & Schüler, 2003). Next, we determine the optimal lag length for the univariate GARCH-models, and fit a GARCH (1,1) model with a skewed-*t* distribution (Hansen (1994) distribution to the standard errors, which takes care of the presence of skewness in the series. Thus, for each marginal model we obtain seven parameters: two parameters (μ, φ) for the conditional mean equation, three parameters $(\omega, \alpha_1, \beta_1)$ for the conditional variance equation, and two distributional parameters, ν and ξ for tail and asymmetry respectively.

Table 3 shows the estimated parameters for ARMA-GARCH models employed to shape the return series. All the series are fitted with an ARMA(1,0)-GARCH(1,1) model. The inclusion of the autoregressive terms is to explain the turbulence caused during the early 2000s and subprime crisis. According to Bollerslev (1986), the following inequality restrictions must be satisfied to ensure that the GARCH (1,1) model is not misspecified: (i) $\varpi_0 \geq 0$ (ii) $\alpha_1 \geq 0$ (iii) $\beta_j \geq 0$ (iv) $\alpha_1 + \beta_1 < 1$. In this regard, all the estimated coefficients (see Table 5) satisfy the standard conditions. The volatility updating parameter, α_1, ranges between 0.0584 to 0.3499 whereas the autoregressive variance parameter, β_1, ranges from 0.65 to 0.9416. The parameter estimates indicate that the GARCH model captures the high volatility persistence in the 12 banking sectors. The sum of the ARCH and GARCH coefficients, $\alpha_1 + \beta_1$, indicates that shocks to volatility have a persistent effect on the conditional variance. In other words, periods of high volatility in the prices will last for a long time. The tail parameter,v, for the innovations is significant for all markets whereas the asymmetry parameter, ξ, is insignificant for some markets.

Table 3 Marginal Models

	China	Hong Kong	Malaysia	Sri Lanka	Indonesia	India	Japan	Korea	Philippines	Singapore	Taiwan	Thailand
Panel A: Conditional Mean												
μ	0.0000	0.0003	**0.0005**[b]	0.0001	**0.0009**[b]	**0.0011**[b]	0.0000	0.0005	0.0004	0.0003	0.0002	**0.0008**[b]
	(0.167)	(1.4521)	(4.2573)	(0.5865)	(2.9104)	(3.9011)	(0.0015)	(1.4311)	(1.7968)	(1.2128)	(0.7653)	(2.7756)
φ	-0.0100	0.0186	**0.0864**[b]	**0.0959**[b]	-0.0007	**0.0943**[b]	**0.0815**[b]	**0.0647**[b]	**0.0755**[b]	-0.0092	**-0.0592**[b]	**0.0488**[b]
	(-1.1062)	(1.3809)	(4.9666)	(5.4939)	(-0.0559)	(5.2172)	(4.5293)	(3.8776)	(3.9915)	(-0.1737)	(-3.5879)	(2.4525)
Panel B: Conditional Variance												
ω	0.0000	0.0000	0.0000	**0.0000**[b]	**0.0000**[b]	**0.0000**[b]	0.0000	0.0000	**0.0000**[b]	0.0000	0.0000	**0.0000**[b]
	(0.7221)	(0.0551)	(1.6026)	(4.0669)	(2.4764)	(2.6506)	(.9499)	(1.8347)	(3.6989)	(1.1854)	(1.6632)	(2.2031)
α_1	0.0752	**0.0484**[b]	**0.0747**[b]	**0.3499**[b]	**0.1275**[b]	**0.1156**[b]	**0.1033**[b]	**0.0839**[b]	**0.1452**[b]	**0.1467**[b]	**0.0652**[b]	**0.1054**
	(1.7146)	(5.0866)	(3.4912)	(6.2288)	(4.6426)	(5.8294)	(2.2766)	(3.6248)	(5.7285)	(3.2498)	(5.2362)	(4.8129)
β_1	**0.9062**[a]	**0.9416**[a]	**0.9153**[a]	**0.6500**[a]	**0.8625**	**0.8553**[a]	**0.8805**[a]	**0.8991**[a]	**0.7825**[a]	**0.8233**[a]	**0.9294**[a]	**0.8686**[a]
	(12.9044)	(79.4972)	(34.7022)	(11.3802)	(31.9449)	(29.946)	(14.0006)	(29.4041)	(21.5594)	(11.5372)	(56.4708)	(27.9727)
$\alpha_1 + \beta_1$	0.9814	0.9900	0.9900	0.9999	0.99000	0.9709	0.9838	0.9830	0.9277	0.9700	0.9946	0.9740
Panel C: Distributional Parameters												
υ	**3.7383**[a]	**4.5470**[a]	**4.3295**[a]	**2.8173**[a]	**4.5687**[a]	**6.1805**[a]	**6.6480**[a]	**5.4539**[a]	**4.0340**[a]	**7.3201**[a]	**4.8406**[a]	**5.1776**[a]
	(13.3400)	(11.7700)	(14.9581)	(22.8878)	(9.263)	(8.8426)	(6.6982)	(8.3019)	(10.7935)	(5.998)	(13.4923)	(7.7326)
ξ	**0.0382**[b]	-0.0092	0.0064	0.0308	0.0222	0.0145	**0.0532**	**0.0532**	0.0326	0.0087	0.0331	**0.0905**
	(2.037)	(-0.4973)	(0.3473)	(1.8361)	(0.8521)	(1.8491)	(2.2931)	(2.9031)	(1.1378)	(0.1288)	(1.3586)	(4.346)

Note: The table presents results for daily returns on the Asian banking sector indices over the period January 2000 to December 2012. The top panel presents the parameter estimates for the conditional mean, modelled by an AR(1) model; the second panel presents parameter estimates from GARCH(1,1) models for the conditional variance, along with the parameter estimates skewed-*t* models for the distribution of the standardized residuals. Figures shown in parenthesis are the t-values. [a] and [b] denote statistical significance at 5% and 10% respectively

After fitting the required marginal models, we proceed, by using the IFM method, to transform the standardized *iid* residuals from the GARCH filtration to uniform margins. In order to test for goodness-of-fit for the marginal models, we carry out the Breusch-Godfrey Serial Correlation LM Test at 20 lags for four moments of the PITs (u) of the standardized residuals from the marginal models; that is $(u - \bar{u})^k$ for $k = 1,2,3,4$.

The p-values from the BGLM test, shown in Table 4, mostly exceed the 5% critical level, which indicate the absence of serial correlation in the PITs. The few exceptions are the four moments for Sri Lanka, second moment and fourth moment for Malaysia, third moment for Philippines and Taiwan. The estimates generally indicate that the marginal models are rightly fitted and hence the PITs can be used in estimating the bivariate copula.

Table 4: Goodness of Fit Tests

Breusch-Godfrey Serial Correlation LM Test p-value				
	First moment	Second moment	Third moment	Fourth moment
China	0.3214	0.5448	0.2444	0.8486
Sri Lanka	0.0000	0.0391	0.0000	0.2319
Hong Kong	0.6678	0.7222	0.7464	0.7784
Indonesia	0.6805	0.0971	0.5859	0.2003
India	0.6892	0.8215	0.1104	0.8453
Japan	0.5209	0.6631	0.5842	0.7462
Korea	0.2719	0.7978	0.2254	0.7227
Malaysia	0.5807	0.0237	0.0734	0.0042
Philippines	0.0561	0.8569	0.0087	0.9404
Singapore	0.4674	0.6912	0.4681	0.1065
Taiwan	0.2839	0.2815	0.0468	0.4932
Thailand	0.3607	0.3277	0.0827	0.6896

Note: The table presents p-values from test for serial correlation in the standardized residuals of the Asian banking sector indices, based on the Breusch-Godfrey Serial Correlation LM at 20 lags. The test is carriedout for four moments, which are shown in the columns accordingly.

5.2. Average Copula Correlations across all markets

The copula estimations were carried out on bivariate data sets for the Asian banking sector stocks indices. Figure 4 presents the time series equal-weighted averages of the pairwise dynamic copula dependence across the 12 Asian countries from January 4, 2000 to December 31, 2012. The top panel shows results for the absolute dependence, the middle and lower panel shows the lower and upper tail dependence, respectively, estimated from the symmetrized Joe Clayton copula across all the Asian markets from January 4, 2000 to December 31, 2012. For each panel, the average across all 12 markets in shown by the black line whereas the lower tail and upper tail dependence are shown by the light grey and deep grey, respectively.

The average dynamic copula dependence in Figure 4 show considerable variations over time and the dependence mostly spike up during periods of financial crisis. The top panel shows that average absolute dependence, estimated with the Gaussian copula across all markets, increased from approximately 0.134 in the second week of October 2008 to approximately 0.383 in the third week of October 2008. Other notable spikes for the average absolute dependence are 0.272 in September 2001, 0.323 in May 2004, 0.344 in August 2007 and 0.341 in October 2011, all of which coincide with major crisis in the global financial markets. The panel also shows that developed markets in Asia have been more association than the emerging markets over the years.

The middle panels show that lower tail correlations are higher than in developed markets than in emerging markets over all periods. The evolution path however is similar across all the groupings and the peaks are all recorded in May 2004. The effect of the previous crises events – both early and late 2000s – are also clearly reflected with significant peaks.

The lower panel of Figure 4 presents the upper tail SJC correlations. Regarding the market grouping, it can be seen that developed markets are more correlated at the upper tails than emerging markets over the years, even though the evolution path is somewhat similar.

Figure 4 also indicates that dependence at the tail ends is generally lower compared with the absolute dependence. For instance, the SJC lower tail peaks at approximately 0.171 whereas the upper tail peaks at 0.117, all of which was recorded in May 2004. Over all, figure 4 shows that dependence, from all sides of the joint distribution, has not been trending up across the banking sector in Asia.

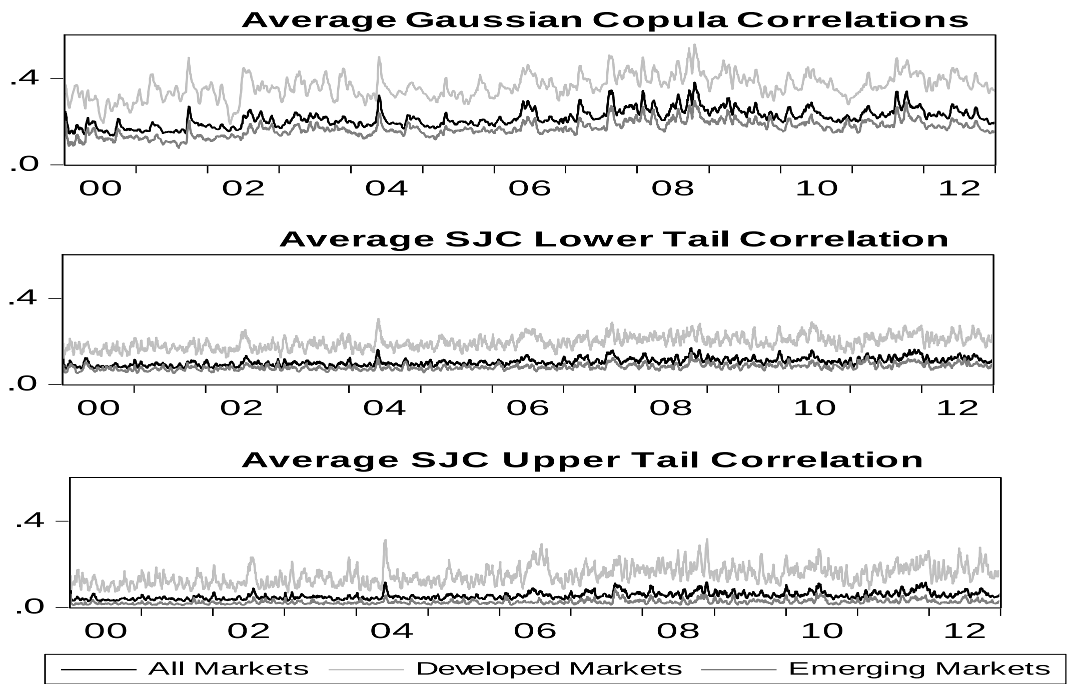

Figure 4: Gaussian and SJC Copula Dependence for All Markets, 2000-2012

5.3. Cross-Sectional Variations in Copula Dependence

Having explained the average dependence across all markets in the previous sections, we now explore the correlation dynamics for each country. The analyses in this section examines whether there are differences in the evolution path of copula dependence across the Asian banking sectors. For each market, we compute equal-weighted averages of corresponding pairwise dependence with the remaining markets and the results are highlighted in Figure 5.

Figure 5 presents the dynamic copula dependence for the banking sector indices from the 12 Asian markets for the period January 4, 2000 to December 31, 2012. For each country we report the average Gaussian copula dependence with 11 remaining countries (light grey line), lower tail dependence of symmetrized Joe-Clayton copula (dark grey line) and upper tail dependence of the symmetrized Joe-Clayton copula (black line). With the results presented in Table 5, it is evident that an upward trend in dependence is not so conspicuous, although there are sharp rises and falls during and after crisis events. For instance, the higher amplitudes observed in the dynamic dependence from mid-2007 to last quarter of 2008 was occasioned by the sub-prime crisis and global financial crisis. A similar pattern is observed during the latter end of 2011 and early 2012, which is attributable to the European Debt crisis. Most of the crisis periods captured in this instance were caused by markets outside the Asian region, specifically USA and European markets. Therefore, this increase in dependence among Asian banking sectors in response to financial crisis caused outside their geographical region indirectly shows how vulnerable the region is to external shocks, which eventually has the potential of causing systemic risk in the region.

The plots contained in Figure 5 also indicate that absolute dependence, estimated with the Gaussian copula, is always higher than the tail end dependence, computed from the SJC copula. Regarding dependence in joint probability distribution at tails, dependence in the lower tails is generally larger than that of the upper tails for all countries, except Sri Lanka where the tail dynamics are too low to display. Lower tail is related with losses and is the major concern for risk managers. Thus, it would be desirable for investors to make allowance for the comovement at the lower tails of the join distribution when selecting assets for ones portfolio.

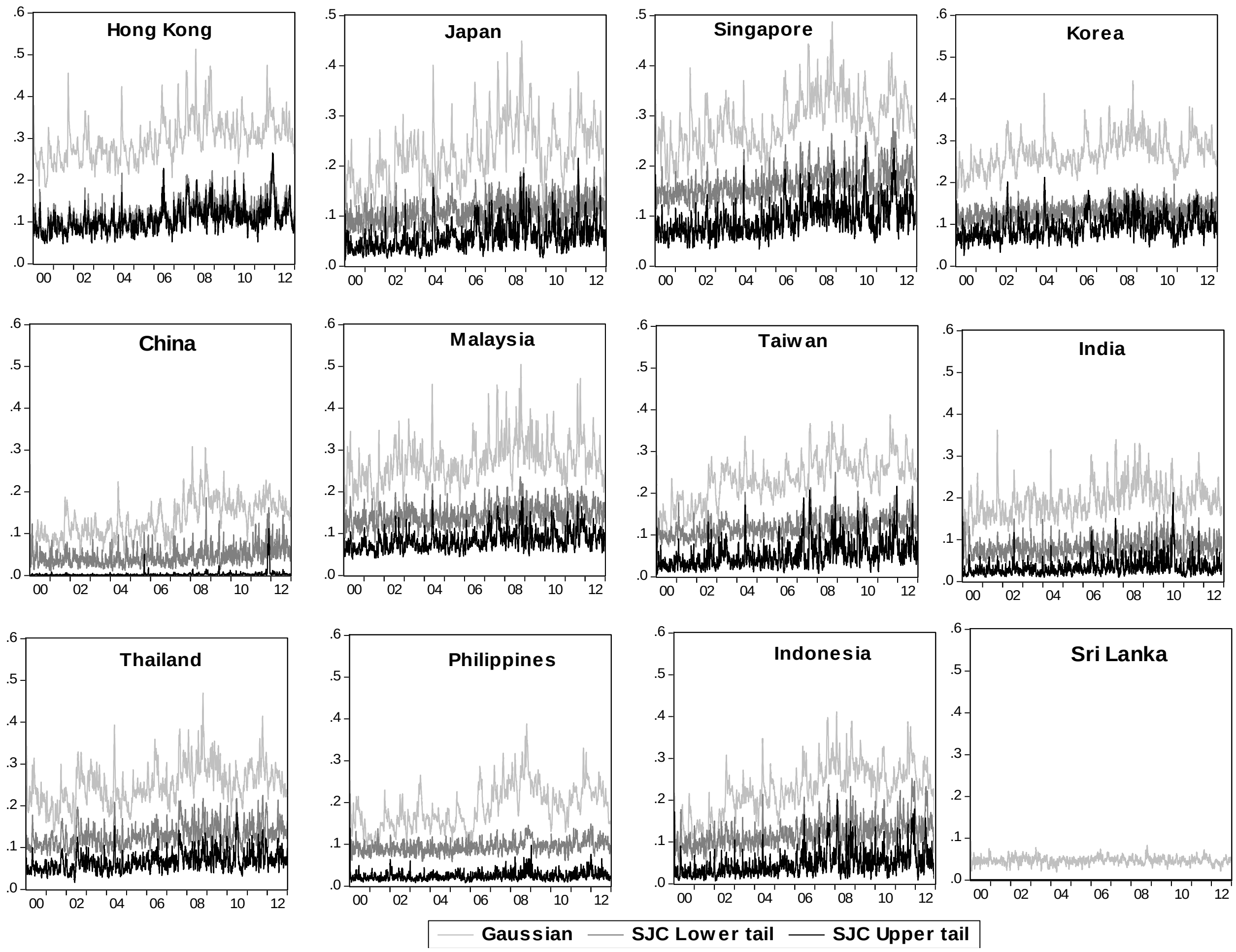

Figure 5: Average Pairwise Dependence for Asian Banking Sectors, Jan 00-Dec 12

5.4. Results from Gaussian Copula for Selected Pairs

From the previous sections, we have uncovered the average pattern of dependence across the all markets. Results presented in Figures 4 and 5, although informative, do provide all the needed information much about the market-by-market dependence. It could be that although the aggregated correlation does not show any upward trend, individual pairs might give a different picture. This section reports the results from the copula estimations for selected pairs of countries[3]. It is not feasible to present all the 66 pairs and so we select a few which are worth highlighting. Tables 5-8 presents the estimated paramers, along with AIC, BIC and log-likelihood for the selected copula models. Panel A of Tables 5-8 presents the paramter estimates

[3] The copula models were estimated using the Copula Toolbox provided by Andrew Patton and the Dynamic Copula Toolbox 3.0 provided by Manthos Vogiatzoglou. All estimations were done with Matlab software.

for the time-varying Gaussian joint copulas. The parameters α and β define the evolution of the copula dependence for the various pairs. For all the country pairs, the persistence parameter, β, is relatively larger compared to the variation coefficient, α; that is, ranges from 0.904 for HK-MY (table 6) to 0.997 for CH-JP (table 5). This effect is reflected in the correlation dynamics overtime shown in upper panels of Figures 6-22.

The top panels of Figures 6-22 presents the time path of the dependence structures shown by the blue lines along with the constant Gaussian copula dependence, shown by the red horizontal lines. Some comments on a few of the upper panels of Figures 6-22 are in order. The time path for CH-HK pair (Fig 6) fluctuates around a constant Gaussian copula of 0.2. It rises fiercely (0.4) in November 2001 (shown by the 500 tick on the horizontal axis), reaches its highest peak (0.5) in the first quarter of 2008 concurrently with the Global Financial crisis, and have since been around 0.3. The CH-JP pair ranges between -0.09 – 0.4 with a constant Gaussian copula dependence of 0.13. Noticeably, it peaks at 0.32 around first quarter of 2004, 0.4 around first quarter of 2008 and 0.39 around October 2008 coinciding with the Global Financial crisis. The time path for HK-IN Gaussian dependence reaches its peak (0.6) in 2001, which happens to be the year of the crash of the dot com bubble. HK-JP pair also fluctuates widely, ranging between 0.01-0.65 around a constant of 0.35. The HK-SG pair also reaches its highest peak (0.68).

It can be noticed that the dependence structure varies considerably over time around the constant Gaussian copula and most often rising fiercely during turbulent times. On the contrary, the banking sectors across the markets seem have a relatively low correlation during tranquil market periods. It is worth noting that, most of these financial turmoils did not originate from Asia but from markets in Europe and North America. Therefore, the fact that Asian markets respond together to such external events signals the extent of their overall dependence on external shocks.

5.5. Symmetrised Joe-Clayton for Selected Pairs

The parameter estimates of upper tail (τ^U) and lower tail (τ^L) dependence based on the static SJC copula are presented panel B1 of Tables 5-8.   In general the lower tail dependence tend to be statistically significant compared to the upper tail dependence. The upper tail dependence spans from 0.0088 (CH-HK) through 0.2325 (HK-SG) whereas the lower tail dependence range from 0.0255 (CH-HK) to 0.2278 (KO-JP).

The joint copula parameters for some market pairs have higher lower tail dependence compared with upper tail dependence. For instance, lower tail dependence for CH-HK (0.0255) is more than twice higher than the upper tail; HK-ID has 0.0955 lower tails against 0.0851 upper tails; HK-TA shows 0.1269 at lower tail as against 0.1009; KOR-JP 0.2278 lower tail versus 0.1208 upper tail; SG-JP has lower tail dependence of 0.197, which is over 3 times higher than the upper tail dependence. This observation of left tail dependence in extreme events implies that these Asian market pairs are more likely to crash together. Moreover, this finding is in line with Longin and Solnik's (2001) who propose that the relatively higher lower tail correlation implies that the increasing dependence across the markets is due to a bear market state rather than volatility.

On the contrary, some of the market pairs display higher upper tail dependence compared to lower tail dependence. For instance, HK-JP show τ^U value of 0.1236 compared with τ^L of 0.1277; HK-KO shows 0.1901 and 0.177 for τ^U and τ^L respectively; HK-SG displays 0.2325 and 0.2255 for τ^U and τ^L in that order; and HK-MY shows 0.1373 τ^U compared with 0.1101 for τ^L. This result implies that there is a higher possibility of joint extreme events in a rising markets rather than in a falling market.

Some market pairs – CH-JP, CH-KO, CH-SG, HK-PH and HK-TH do not have significant right tail dependence, implying that they are not susceptible to joint extreme events during bull markets. HK-CY pair does not show significant tail dependence.

Panel B2 of Tables 5-8 presents the parameter estimates for the time-varying SJC. The corresponding dependence time paths are shown in the second and third panels of Figures 6-22.

We see a different picture for the market pairs, which previously had higher constant left tails as opposed to right tails. For instance, the time path for HK-ID looks like a white noise process that is generally below 0.3 with somewhat lower the evolution of the right tail dependence. Similarly, KO-JP pair has left tail copula evolution akin to a white noise process with 0.5 as the highest peak. The HK-TA shows a similar path for both upper and lower tail dependence. SG-JP pair shows a similar trend whereas CH-HK lower tail mostly remains low but peaks at 0.7 in 2012. Similarly, the pairs that had higher upper tail comparatively show mixed results in the time path of the tails. For instance, the HK-MY pair shows relatively higher peak for lower tail compared to the upper tail, which is generally below 0.4. HK-SG comparable time path for both tails whereas upper tail for HK-JP remains below 0.4, upper tail for HK-KO ranges between 0.1 to 0.4 with peaks during 2006 , 2008, 2012.

There is consistency for those pairs which had only left tail dependence via the static SJC. The CH-JP and CH-KO time paths shows only lower tail dependence without any upper tail dependence time path. The CH-SG pair has lower tail dependence peaking at 0.5 at end of 2005, 0.45 in the first quarter of 2006 and 2008, 0.65 in early 2012. The upper tail remains very low but with high peaks (0.8) in 2005 and early 2012. HK-PH upper tail remains below 0.1. The lower tail is low as well but peaks at 0.2 in first half of 2012. Other pairs such as HK-CY continue to shows no lower tail dependence overtime. HK-ID also shows peaks in lower tail in 2006 (0.5) and early 2012 (0.45) whereas HK-IN peaks around 0.45 in 2010.

Overall, most of the pairs show higher values for τ^L compared with τ^U, which implies that the extent of dependence in the lower tail of the distributions is substantially greater than the extent of dependence in the positive extremes. These findings show that the Asian regional banking system could be prone to systemic risk, which involves extreme negative events.

The results also show an asymmetric dependence structure across the region; $\tau^U - \tau^L \neq 0$. This coroborates the findings based on the quantile dependence shown in Figure 3. It is also in line with previous studies (Erb, Harvey, & Viskanta, 1994; Longin and Solnik, 2001; Ang and Bekaert, 2002; Ang and Chen, 2002; Das and Uppal, 2004; and Patton, 2004) which find overwhelming evidence of asymmetric dependence in international stock markets. According to Hu (2006) this asymmetry arises because investors react more towards bad news than good news in other markets. The results from the time-varying SJC to a large extent have shown substantial evidence of dependence in both the lower and upper tail distributions of the Asian banking sectors which suggests possible similarities in how banking activities are carried out in the region. In particular, the evidence of lower tail dependence should be a concern as it could aid in the easy spread of contagious shocks across the regional banking system.

Using the Akaike Information Criterion (AIC), the optimal copula model was found to be the time-varying Gaussian copula for all the estimated pairs. The next best fitted turns out to be the time-varying SJC copula for most cases, an indication that the time-varying models can better capture the dependence structure between the banking sector indices.

Table 5: Estimation of Joint copula Parameters

	CH-HK	CH-JP	CH-KO	CH-SG
Panel A: Time-varying Gaussian Copula				
α	0.0079	**0.0031**	**0.0042**	**0.0051**
	(.005)	(.001)	(.001)	(.001)
β	**0.9915**	**0.9967**	**0.9958**	**0.9949**
	(.006)	(.001)	(.000)	(.000)
AIC	-206.9615	-77.7167	-135.4497	-141.0529
BIC	-194.7043	-65.4595	-123.1925	-128.7957
LL	105.481	40.858	69.725	72.526

Panel B1: Static SJC				
τ^U	**0.0088**	0.0000	0.0007	2.30E-03
	(.0000)	(.0000)	(.002)	(.004)
τ^L	**0.0255**	**0.0415**	**0.064**	**0.0477**
	(.011)	(.018)	(.02)	(.02)
AIC	-107.6376	-56.9351	-90.4526	-77.4169
BIC	-95.3804	-44.6779	-78.1954	-65.1598
LL	55.819	30.468	47.226	40.708
Panel B2: Time-varying SJC				
ω^U (upper tail)	-9.9946	**0.3086**	**-9.9915**	-9.9888
	(5.268)	(.362)	(1.213)	(115.654)
α^U	0.1457	-1.2034	-3.8514	0.1113
	(.09)	(.657)	(392.183)	(138.702)
β^U	10	**1.2688**	9.9678	9.9925
	(5.846)	(.406)	(6.231)	(16.874)
ω^L (lower tail)	**0.3428**	**0.7346**	-1.2747	**0.1224**
	(.165)	(.339)	(1.504)	(.028)
α^L	**-1.7545**	**-5.7559**	**-9.9999**	**-0.5256**
	(.913)	(1.875)	(.012)	(.125)
β^L	**0.9724**	**0.7274**	-0.678	**0.9906**
	(.016)	(.076)	(.678)	(.003)
AIC	-125.8151	-59.6811	-88.6853	-94.7901
BIC	-89.0436	-22.9096	-51.9138	-58.0186
LL	68.908	35.841	50.343	53.395

Note: The table presents the estimated parameters of five copulas. Figures in bold are statistically significant at 5% level. The asymptotic standard errors are presented in the parentheses. AIC and BIC are the Akaike and Bayes Information Criteria. The value of the copula log-likelihood (LL) at the optimum is also presented. α and β are the coefficients of the time varying process for the Gaussian copula;$\tau^U$and τ^L refers to the upper and lower tail paramters of the SJC copula.. The parameters ω^U and ω^L correspond to the upper and lowe tail of the time varying SJC, α^U and β^Ucorrespond to the coefficient for the time varying process of the SJC copula at upper tail whereas α^L and β^L apply to the lower tail. CH, China; HK, Hong Kong; JP, Japan; KO, Korea; SG, Singapore.

Table 6: Estimation of Joint copula Parameters

	HK-JP	**HK-KO**	**HK-SG**	**HK-MY**
Panel A: Time-varying Gaussian Copula				
α	**0.0144**	**0.0138**	0.0097	**0.0355**
	(0.0060)	(0.0050)	(0.009)	(0.0210)
β	**0.9783**	**0.974**	**0.9838**	**0.9037**
	(0.0110)	(0.0080)	(0.0200)	(0.0950)
AIC	-519.391	-702.295	-914.9632	-367.73
BIC	-507.134	-690.038	-902.706	-355.473
LL	261.696	353.148	459.482	185.865

Panel B1: Static SJC

τ^U	**0.1236**	**0.1901**	**0.2325**	**0.1373**
	(0.0250)	(0.0070)	(0.0290)	(0.0320)
τ^L	**0.1277**	**0.177**	**0.225**	**0.1101**
	(0.0250)	(0.0260)	(0.0300)	(0.0310)
AIC	-392.205	-593.591	-765.4817	-268.863
BIC	-379.948	-581.334	-753.2245	-256.605
LL	198.102	298.796	384.741	136.431
Panel B2: Time-varying SJC				
ω^U (upper tail)	**0.1698**	**0.1607**	0.5951	0.295
	(0.0250)	(0.0280)	(63953.46)	(0.8510)
α^U	**-0.9003**	**-0.8863**	-10	**-7.2241**
	(0.0180)	(0.0340)	(32284.21)	(2.8880)
β^U	**0.9662**	**0.9592**	-0.958	0.1402
	(0.0150)	(0.0140)	(6025.88)	(0.4390)
ω^L (lower tail)	-0.6465	-0.0242	0.9015	1.082
	(2.1500)	(1.2950)	(98984.44)	(0.6570)
α^L	-9.9983	-8.7199	-9.9998	**-9.9999**
	(8.2110)	(7.4520)	(539867.9)	(3.2860)
β^L	**-0.9747**	**-0.7507**	-0.5456	0.1432
	(0.0740)	(0.0830)	(82508.97)	(0.2640)
AIC	-438.167	-623.234	-791.2689	-294.74
BIC	-401.396	-586.463	-754.4974	-257.969
LL	225.084	317.617	401.634	153.37

Note: The table presents the estimated parameters of five copulas. Figures in bold are statistically significant at 5% level. The asymptotic standard errors are presented in the parentheses. AIC and BIC are the Akaike and Bayes Information Criteria. The value of the copula log-likelihood (LL) at the optimum is also presented. α and β are the coefficients of the time varying process for the Gaussian copula;$\tau^U$and τ^L refers to the upper and lower tail paramters of the SJC copula.. The parameters ω^U and ω^L correspond to the upper and lowe tail of the time varying SJC, α^U and β^Ucorrespond to the coefficient for the time varying process of the SJC copula at upper tail whereas α^L and β^L apply to the lower tail. HK, Hong Kong; JP, Japan; KO, Korea; SG, Singapore; MY, Malaysia.

Table 6: Estimation of Joint copula Parameters

	HK-ID	**HK-TA**	**HK-IN**	**HK-PH**
Panel A: Time-varying Gaussian Copula				
α	**0.0179**	0.0145	**0.0211**	**0.0085**
	(0.0070)	(0.0120)	(0.0060)	(0.0040)
β	**0.9772**	**0.9764**	**0.9592**	**0.9879**
	(0.0110)	(0.0270)	(0.0160)	(0.0060)
AIC	-423.909	-467.84	-324.54	-260.624
BIC	-411.652	-455.583	-312.283	-248.367
LL	213.955	235.92	164.27	132.312
Panel B1: Static SJC				

τ^U	**0.0851**	**0.1009**	**0.0744**	0.0261
	(0.0030)	(0.0230)	(0.0220)	(0.0200)
τ^L	**0.0955**	**0.1269**	**0.0643**	**0.0751**
	(0.0200)	(0.0240)	(0.0200)	(0.0200)
AIC	**-294.015**	**-382.294**	**-230.705**	**-195.116**
BIC	-281.758	-370.037	-218.448	-182.859
LL	149.007	193.147	117.353	99.558
Panel B2: Time-varying SJC				
ω^U(upper tail)	**0.2193**	**0.2606**	**0.1675**	**0.2909**
	(0.0180)	(0.0750)	(0.0140)	(0.0690)
α^U	**-1.1975**	**-1.4368**	**-0.8287**	**-1.7665**
	(0.0870)	(0.4660)	(0.0630)	(0.3900)
β^U	**0.9621**	**0.9533**	**0.9792**	**0.9466**
	(0.0060)	(0.0230)	(0.0040)	(0.0170)
ω^L(lower tail)	0.7249	0.2624	0.8189	-1.0329
	(0.6120)	(1.9080)	(0.7600)	(0.6350)
α^L	-9.8781	-9.9998	**-9.991**	**-4.7603**
	(7.8840)	(17.6140)	(4.1610)	(2.3250)
β^L	0.056	-0.4548	0.2703	-0.0285
	(1.1180)	(1.8490)	(0.1590)	(0.2930)
AIC	-342.542	-417.326	-265.294	-201.882
BIC	-305.77	-380.554	-228.522	-165.11
LL	177.271	214.663	138.647	106.941

Note: The table presents the estimated parameters of five copulas. Figures in bold are statistically significant at 5% level. The asymptotic standard errors are presented in the parentheses. AIC and BIC are the Akaike and Bayes Information Criteria. The value of the copula log-likelihood (LL) at the optimum is also presented. α and β are the coefficients of the time varying process for the Gaussian copula;$\tau^U$and τ^L refers to the upper and lower tail paramters of the SJC copula.. The parameters ω^U and ω^L correspond to the upper and lowe tail of the time varying SJC, α^U and β^Ucorrespond to the coefficient for the time varying process of the SJC copula at upper tail whereas α^L and β^L apply to the lower tail. HK, Hong Kong; ID, Indonesia; TA, Taiwan; IN, India; PH, Philippines.

Table 7: Estimation of Joint copula Parameters

	HK-TH	**HK-CY**	**SG-KO**	**SG-JP**	**KO-JP**
Panel A: Time-varying Gaussian Copula					
α	**0.0085**	0.003	**0.009**	0.0204	**0.0192**
	(0.004)	(0.0020)	(0.0050)	(0.0120)	(0.0050)
β	**0.9879**	**0.9898**	**0.9832**	**0.9687**	**0.972**
	(0.006)	(0.0060)	(0.0110)	(0.022)	(0.0090)
AIC	-260.624	-16.3278	-541.17	-388.964	-534.988
BIC	-248.367	-4.0707	-528.912	-376.707	-522.731
LL	132.312	10.164	272.585	196.482	269.494
Panel B1: Static SJC					

τ^U	0.0261	0.0001	**0.1862**	**0.0563**	**0.1208**
	(0.020)	(3385.239)	(0.0230)	(0.0230)	(0.0260)
τ^L	**0.0751**	0.0002	**0.1872**	**0.197**	**0.2278**
	(0.020)	(1845.591)	(0.0220)	(0.0210)	(0.0220)
AIC	-195.12	-12.4762	-521.723	-349.715	-475.902
BIC	-182.86	-0.219	-509.466	-337.458	-463.645
LL	99.558	8.238	262.862	176.858	239.951
Panel B2: Time-varying SJC					
ω^U(upper tail)	**0.2909**	**-9.9285**	0.2779	1.0953	**0.1942**
	(0.069)	(20.405)	(0.5800)	(1.2820)	(0.0590)
α^U	**-1.7665**	**4.45**	-3.5179	-9.9997	**-0.9921**
	(0.390)	(107.197)	(4.967)	(11.8400)	(0.3150)
β^U	**0.9466**	9.9938	0.4376	0.338	**0.9679**
	(0.017)	(1.818)	(0.662)	(0.8390)	(0.0100)
ω^L(lower tail)	-1.0329	**-9.3195**	-0.2245	-0.0879	1.1164
	(0.635)	(7.737)	(0.5070)	(0.4530)	(0.7400)
α^L	**-4.7603**	**-2.1819**	-1.0897	**-4.321**	**-9.9939**
	(2.325)	(56.266)	(0.6870)	(1.5190)	(3.5640)
β^L	-0.0285	**9.4561**	0.5487	-0.1347	**-0.5014**
	(0.293)	(7.161)	(0.3590)	(0.2340)	(0.1690)
AIC	-201.882	-6.2313	-524.023	-368.445	-527.379
BIC	-165.11	30.5402	-487.251	-331.673	-490.608
LL	106.941	9.116	268.011	190.222	269.69

Note: The table presents the estimated parameters of five copulas. Figures in bold are statistically significant at 5% level. The asymptotic standard errors are presented in the parentheses. AIC and BIC are the Akaike and Bayes Information Criteria. The value of the copula log-likelihood (LL) at the optimum is also presented. α and β are the coefficients of the time varying process for the Gaussian copula;$\tau^U$and τ^L refers to the upper and lower tail paramters of the SJC copula.. The parameters ω^U and ω^L correspond to the upper and lowe tail of the time varying SJC, α^U and β^Ucorrespond to the coefficient for the time varying process of the SJC copula at upper tail whereas α^L and β^L apply to the lower tail. HK, Hong Kong; TH, Thailand; CY, Sri Lanka; SG, Singapore; KO, Korea; JP, Japan.

5.3. Implications for Portfolio Diversification and Systemic Risk

The dependence among markets is of crucial importance in quantifying market risk, credit risk as well as a critical determinant of systemic risk. Systemic risk can be considered as the risk of an entire financial system or financial markets failing in manner that can potential disrupt the real economy. We dwell on the dependence results to address the issue of whether there is systemic risk potential among the banking sectors of the twelve markets examined.

The analysis from the previous sections illustrates how knitted the banking sectors from the twelve economies are. The evidence for the dynamic path of country average copula dependences, shown in Figure 4, indicates that cross-country heterogeneity in the copula correlations/ tail dependence is not so prevalent. In general, the market pairs have not shown any significant upward trends, which suggest that integration has not fully materialized among the Asian markets. This is particularly useful to investors in the sense that gains can be made by holding assets from the Asian banking sectors, which could reduce portfolio risk, particularly during the benign periods.

However, the findings suggest that lower tail dependence is more prevalent than upper tail dependence. Most importantly, Figure 4 indicates that at the height of the crisis in 2008, dependencies across all markets pairs increases more strongly. This finding highlights the importance of proper financial management because portfolios that are deemed well diversified in calm periods could experience sharp increases in correlation, which will result in unexpected loss owing to the combined, highly correlated decline of several stocks during turbulent times.

Moreover, the large increases in tail correlations owning to crisis to financial crises, which did not have Asian markets as its epicentre, suggest that the banking sectors across the region can be hard-hit or face simultaneous disruption in response to external contagious shocks.

6. Conclusion

This study examines the dependence structure across banking sectors in 12 selected Asian economies including Hong Kong, Singapore, Japan, China, Taiwan, India, Indonesia, Korea, Malaysia, Philippines, Thailand and Sri Lanka. Three copula models – time varying Gaussian Copula, static symmetrized Joe-Clayton and time-varying SJC – are applied to model the entire dependence structure, along with the tail dependence. The marginal are fitted with AR-GARCH models with a skewed-*t* distribution for the standardized residuals. A number of findings and implications from the above analysis are worth highlighting.

To begin with, the level of lower tail dependence is fairly higher than upper tail dependence, indicating asymmetry in dependence. However, the dynamic paths as defined by the SJC copula do not trend upwards. Rather, the tail dependence increases significantly – shows sharp spikes – in response to financial crises, suggesting that there could be joint crashes in the regional banking system during extreme negative events. Considering the fact that most of the past major financial crises – subprime crisis, and Eurozone Debt Crisis – did not begin from Asia, the broader implication of this finding is that the banking sectors across the region can be rendered fragile simultaneously or jointly crash in response to external shocks.

Given the significant absolute and tail dependence across the regional banking sector, policies that maximize resilience to shocks while exploring the benefits of greater integration (such as risk sharing) are worth pursuing. With the high synchronization of the banking sectors pairs during crisis times, shown by the estimated tail dependence, it is likely that shocks could affect individuals markets easily or spillover to the region as whole. In the event that it happens, there could be concurrent external financing pressures depending on the type of shocks. This can be mitigated by having a regional body that provides safety nets to ensure stability within the financial system. An example is the Chiang Mai Initiative Multilateralisation, set up by the ASEAN economies (IMF, 2014).

Furthermore, the results of the marginal models suggest strong volatility persistence in all twelve markets. The Gaussian copula parameters also indicate high persistence in the absolute dependence of among market pairs. The findings also suggest that time-varying copulas are best suited for modelling the dependence structure of the Asian banking sector indices compared with static copula. As expected, both the AIC and BIC shows the two best fitting copula models to be of time-varying structure. Fitting a time-varying copula provides better insight into the dependence structure between the sectors and particularly shows how it varies during tranquil and crises periods.

Generally, the result from this study is sufficient to conclude that absolute and tail dependence is not trending up much across the banking sectors; it remains at moderate levels. Although tail dependence is generally low, it increases rapidly during financial crises. Dependence has been of essential importance to economics particularly following the introduction of the Capital Asset Pricing Model (CAPM) and mathematical theory of portfolio allocation. The findings from this paper are of importance for international diversification, cross-sector risk management, asset pricing, which hinges on understanding dependence in order to minimize the risk of specific assets through optimal resource allocation.

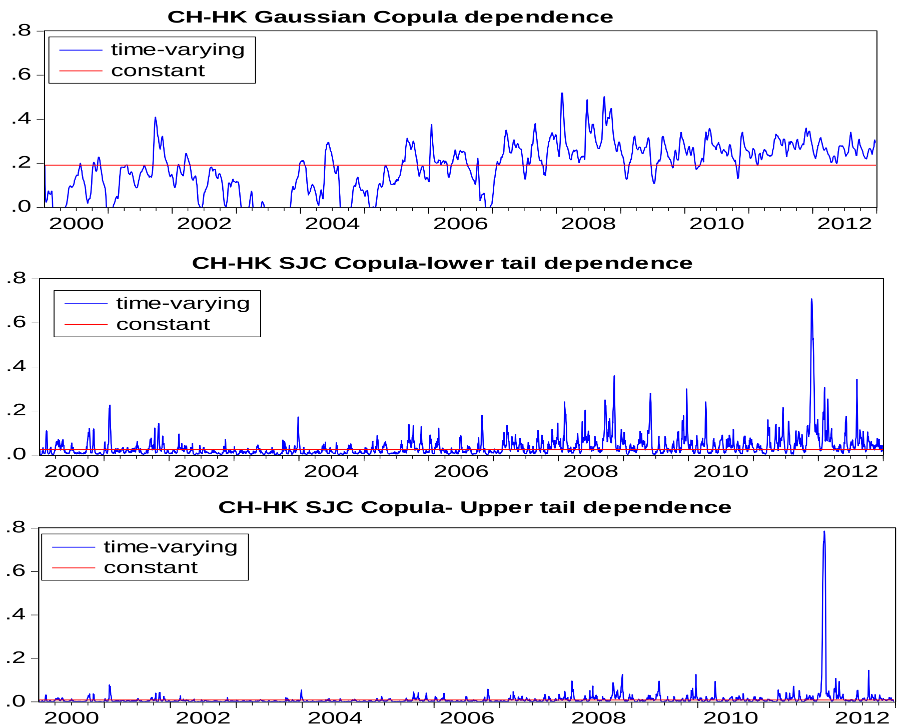

Figure 6: Evolution of time varying copulas of China and Hong Kong

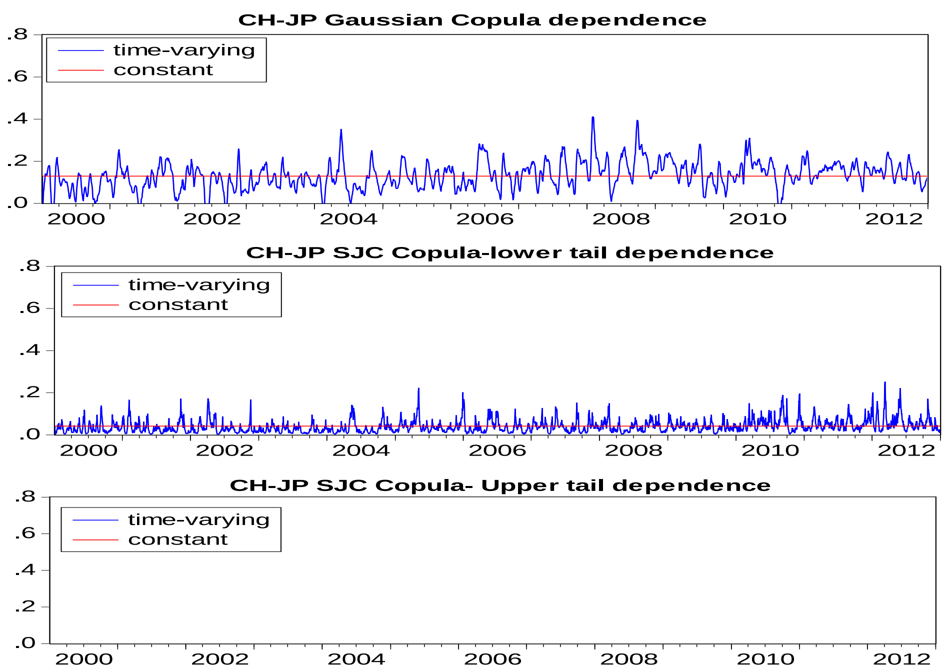

Figure 7: Evolution of time varying copulas of China and Japan

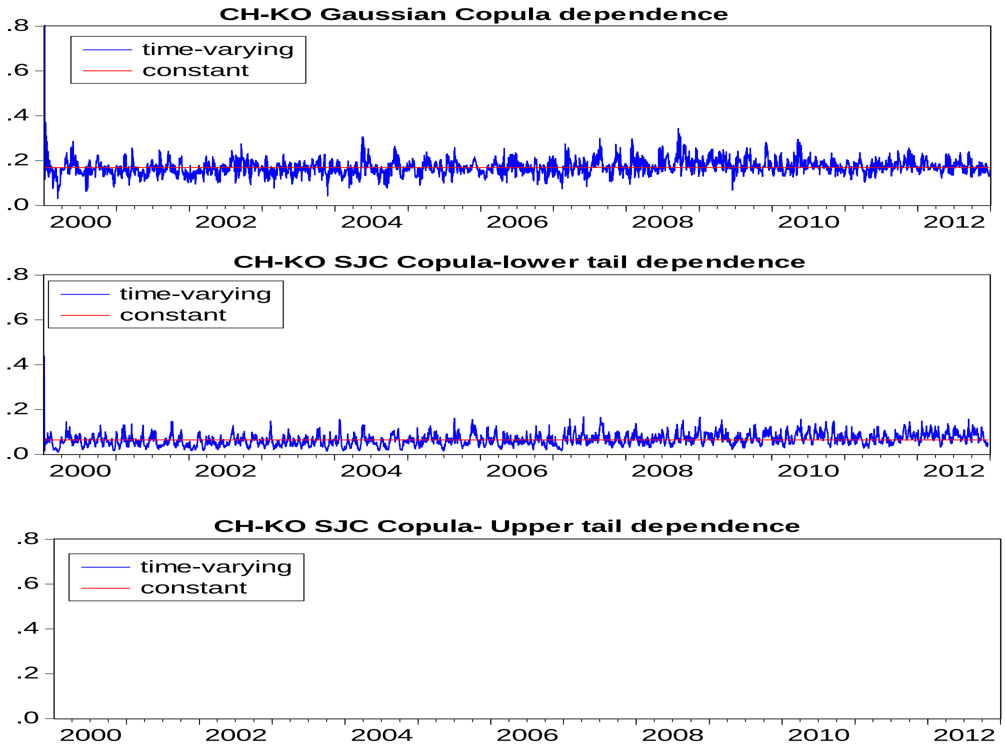

Figure 8: Evolution of time varying copulas of China and Korea

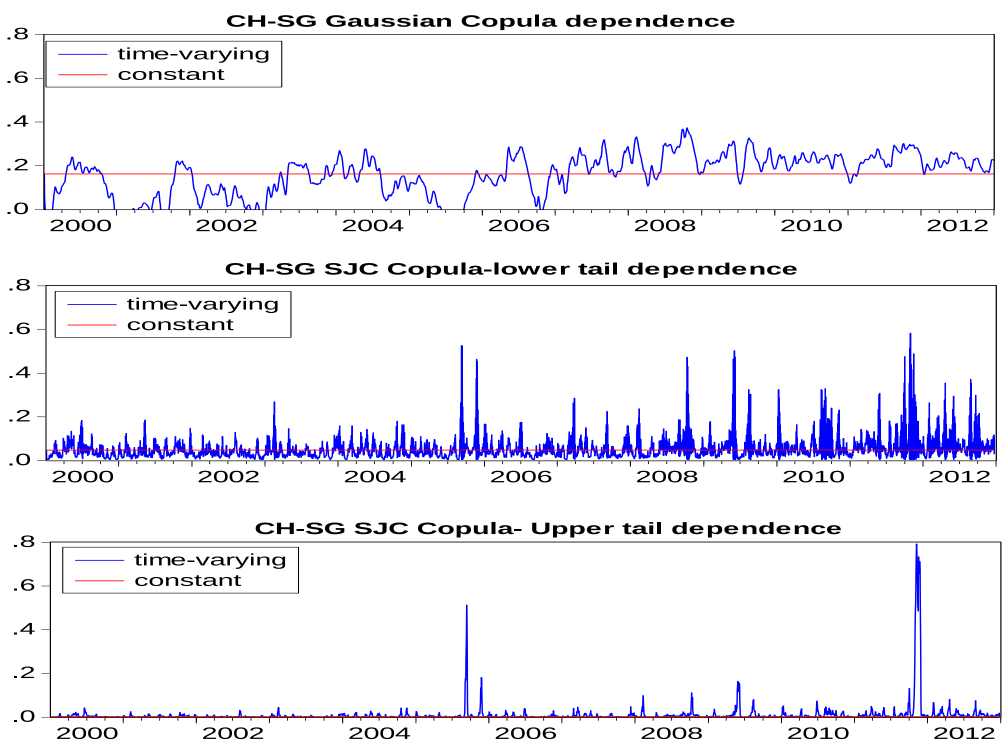

Figure 9: Evolution of time varying copulas of China and Singapore

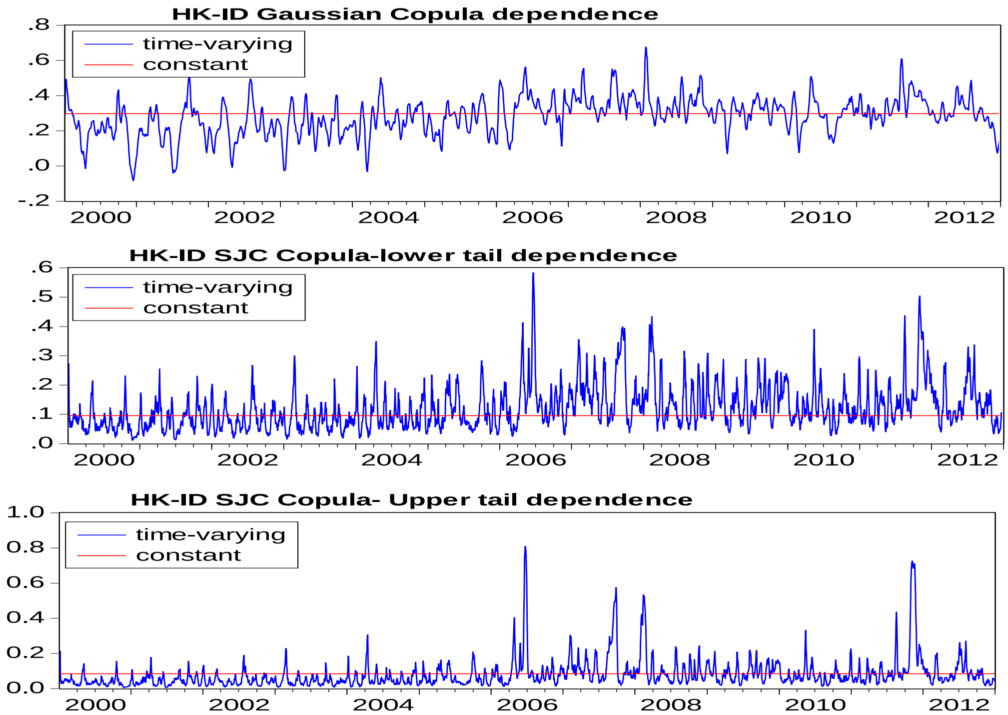

Figure 10: Evolution of time varying copulas of China and Indonesia

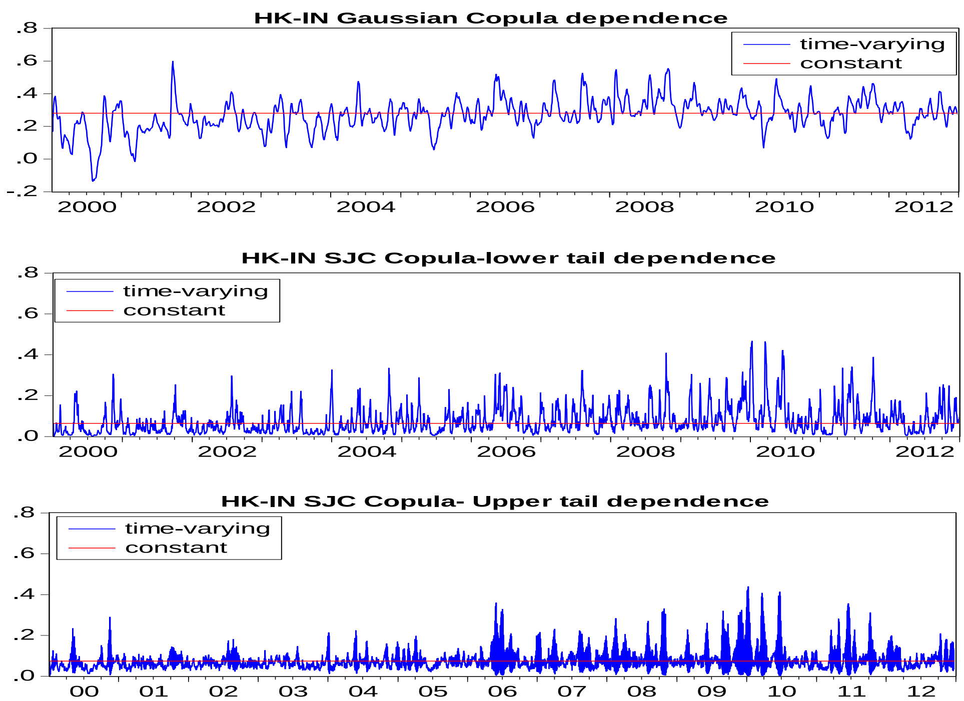

Figure 11: Evolution of time varying copulas of Hong Kong and India

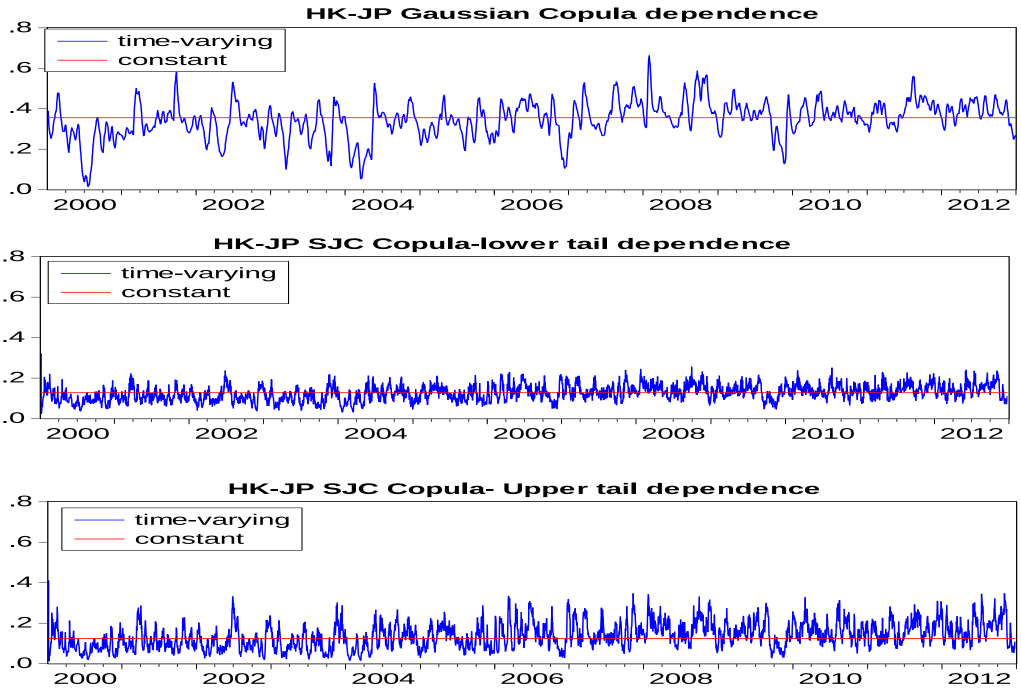

Figure 12: Evolution of time varying copulas of Hong Kong and Japan

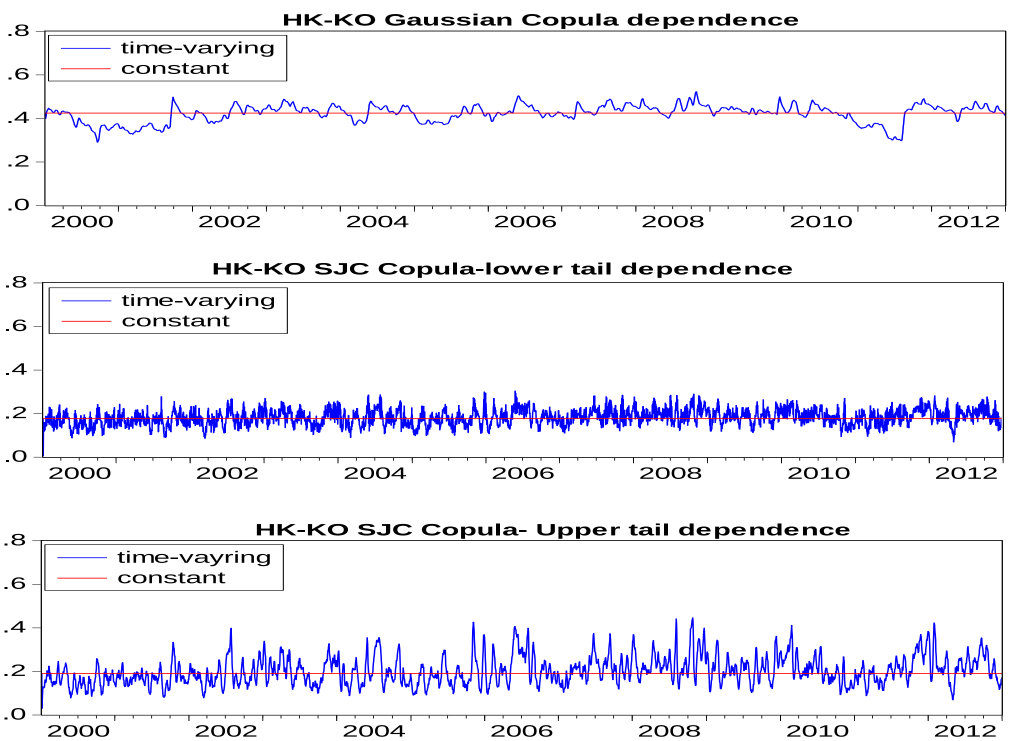

Figure 13: Evolution of time varying copulas of Hong Kong and Korea

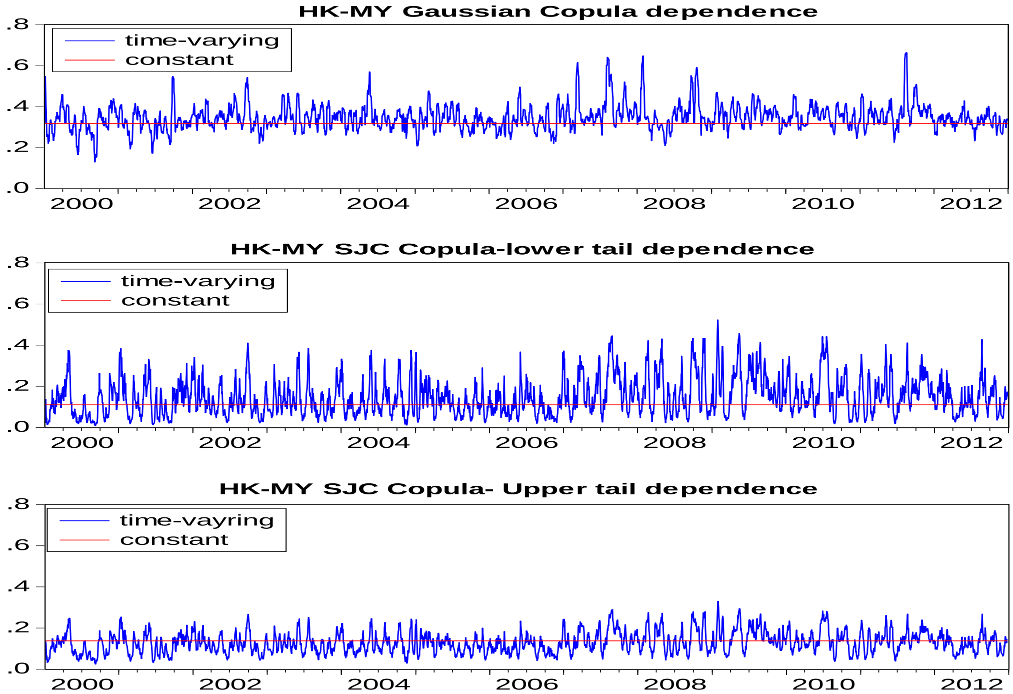

Figure 14: Evolution of time varying copulas of Hong Kong and Malaysia

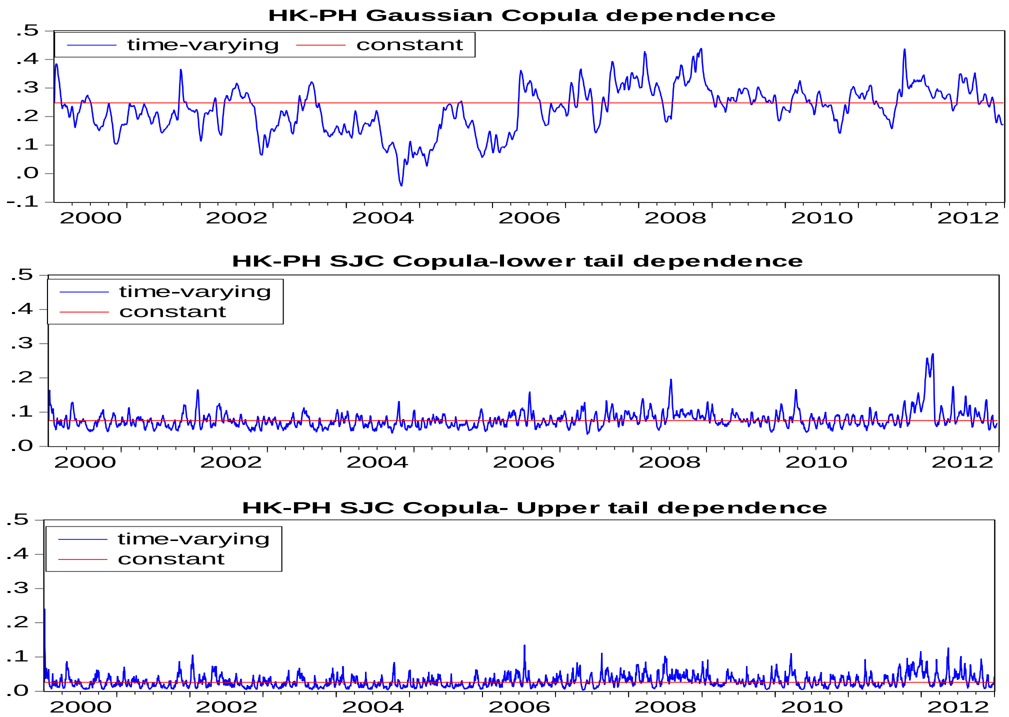

Figure 15: Evolution of time varying copulas of Hong Kong and Philippines

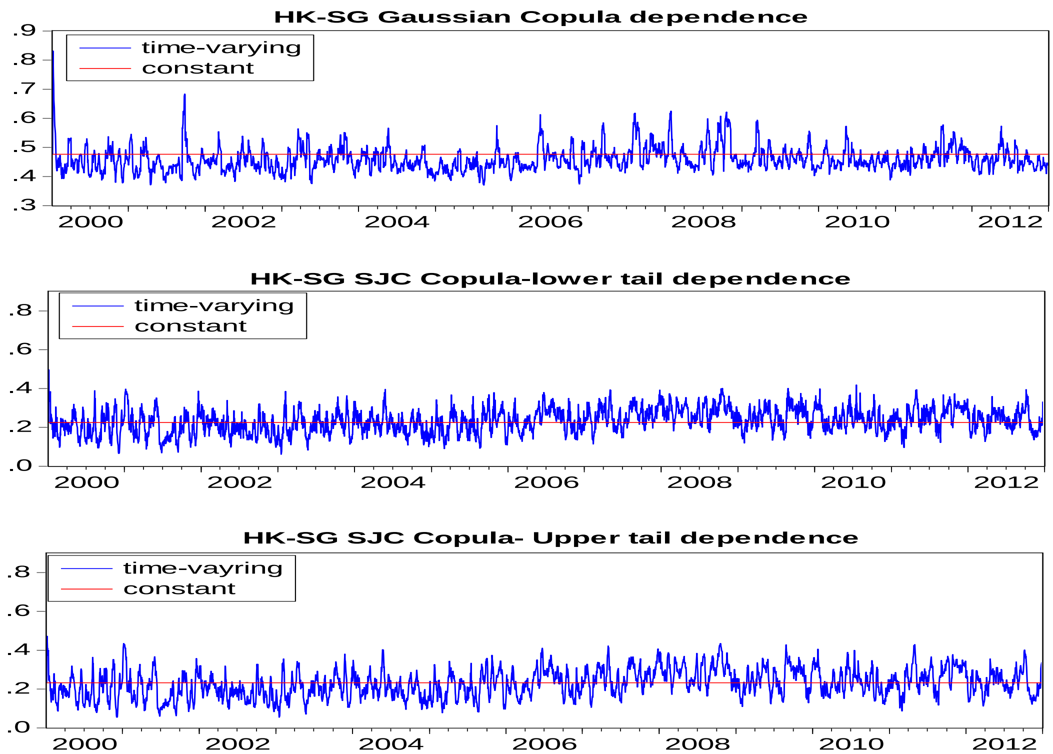

Figure 16: Evolution of time varying copulas of Hong Kong and Singapore

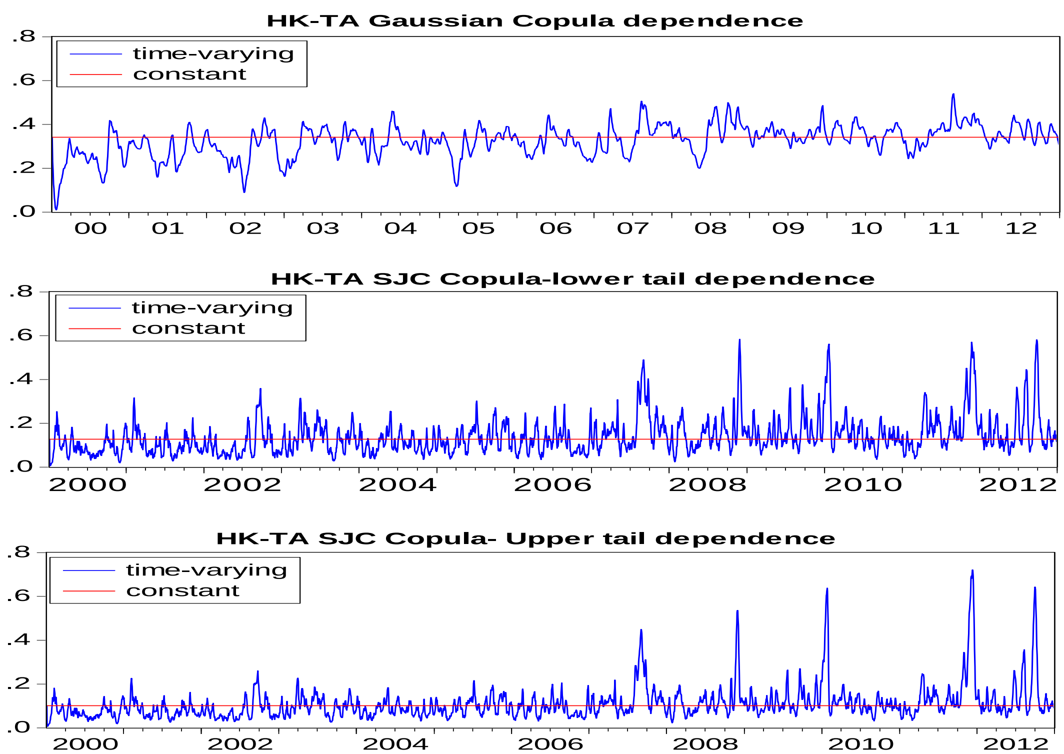

Figure 17: Evolution of time varying copulas of Hong Kong and Taiwan

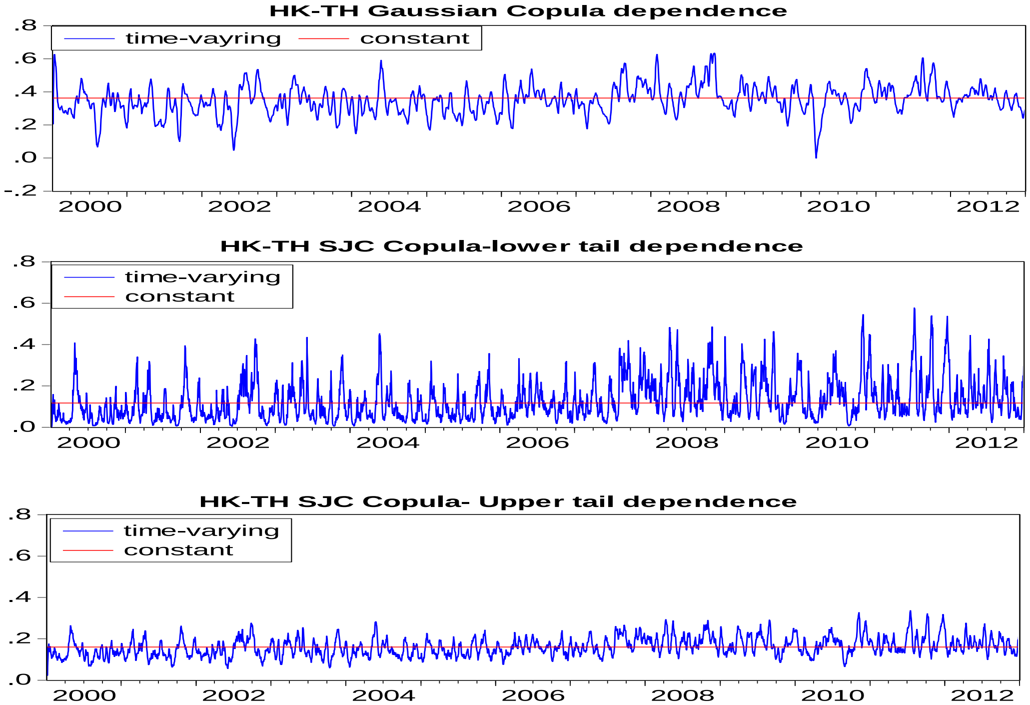

Figure 18: Evolution of time varying copulas of Hong Kong and Thailand

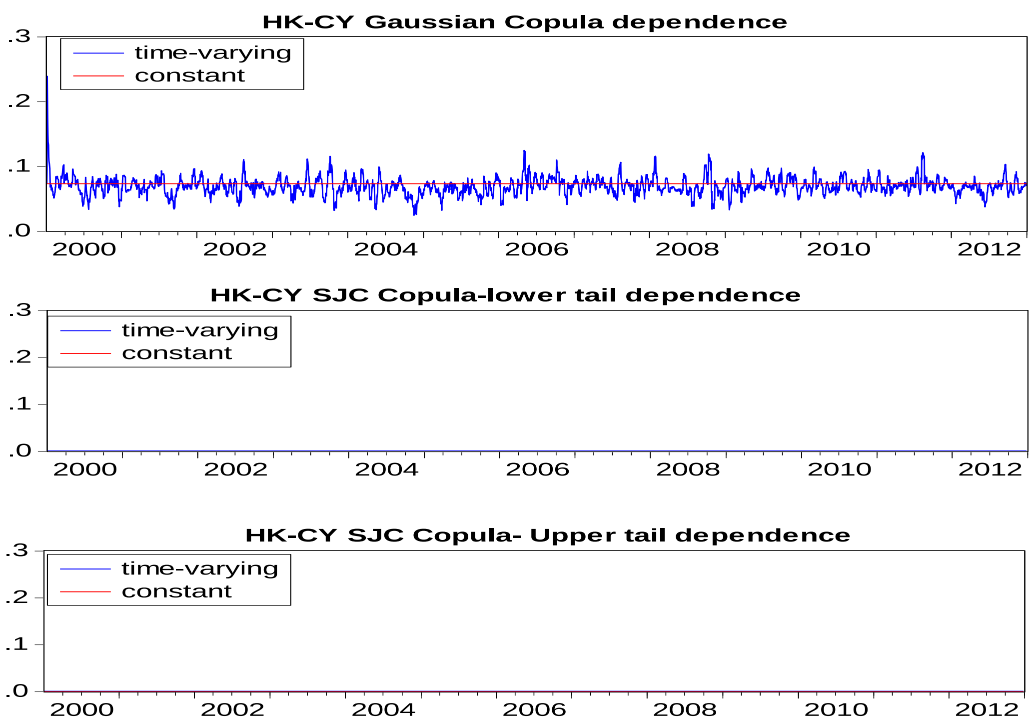

Figure 19: Evolution of time varying copulas of Hong Kong and Sri Lanka

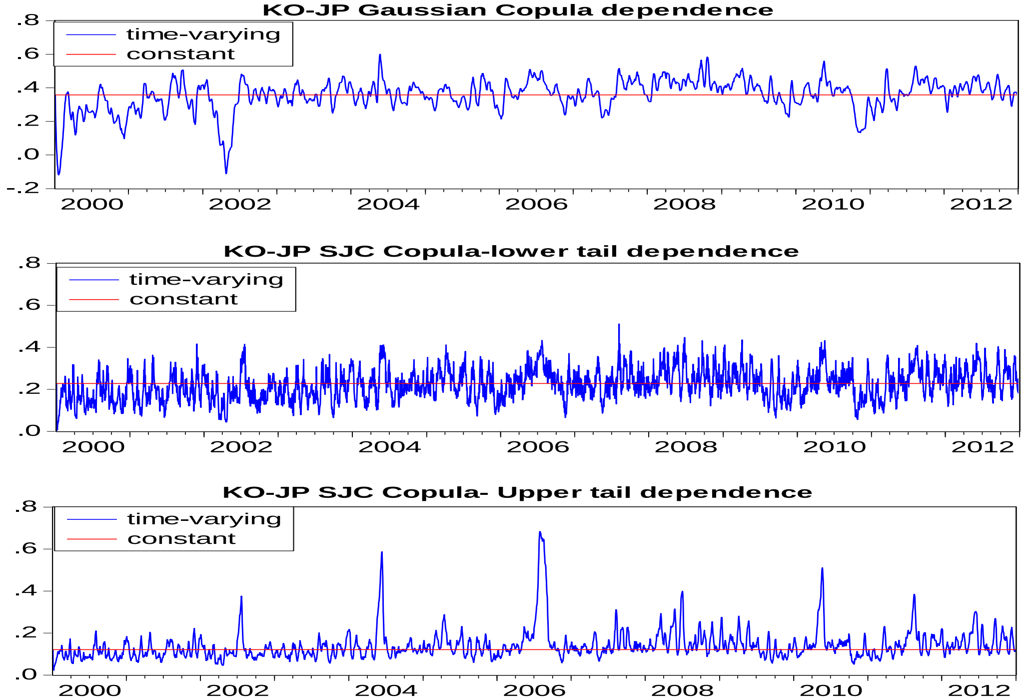

Figure 20: Evolution of time varying copulas of Korea and Japan

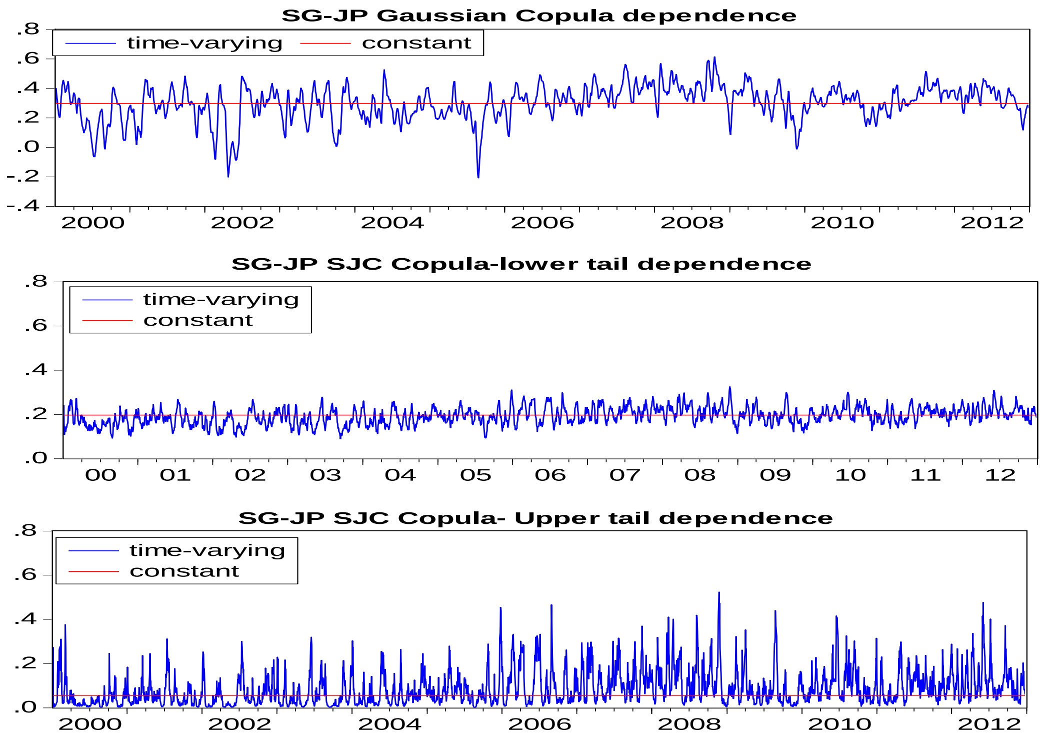

Figure 21: Evolution of time varying copulas of Singapore and Japan

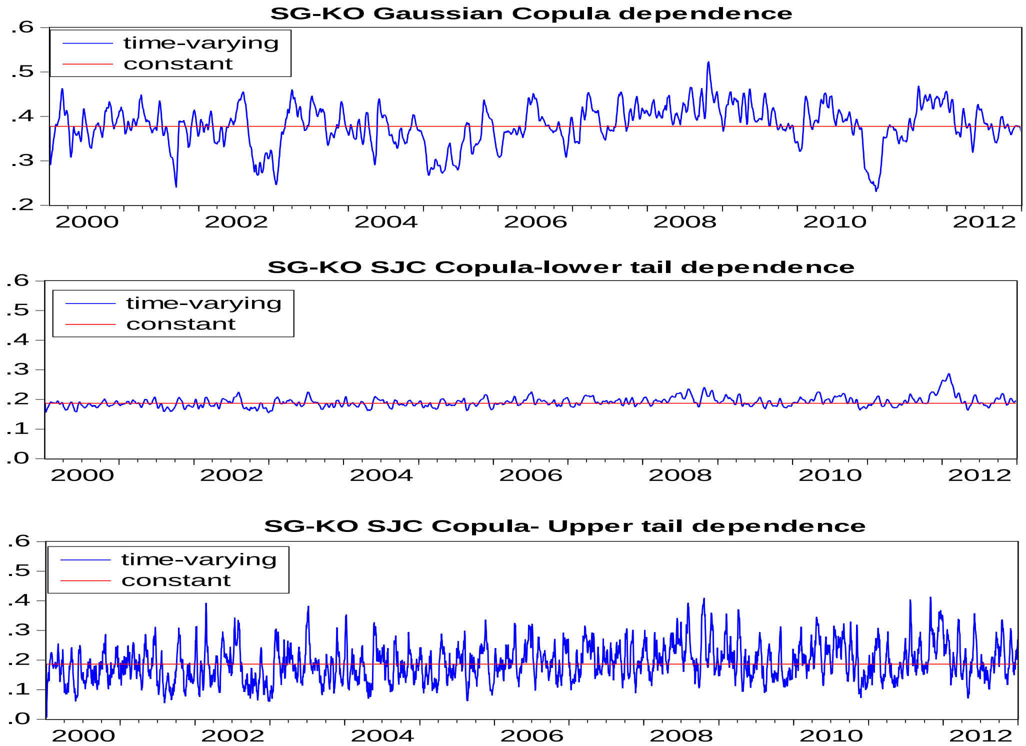

Figure 22: Evolution of time varying copulas of Singapore and Korea

References

Adrian, T., & Brunnermeier, M. (2010). *CoVaR.* (Working Paper, Federal Reserve Bank of New York).

Aielli, G. (2009). *Dynamic conditional correlations: on properties and estimation.* (University of Florida Working Paper).

Ang, A., & Bekaert, G. (2002). International asset allocation with regime shifts. *Review of Financial Studies*, *11*, 1137–1187.

Ang, A., & Chen, J. (2002). Asymmetric correlations of equity portfolios. *Journal of Financial Economics*, *63*, 443-494.

Baele, L., & Inghelbrecht, K. (2009). Time-varying Integration and International diversification strategies. *Journal of Empirical Finance*, *16*(3), 368-387.

Baele, L., & Inghelbrecht, K. (2009). Time-Varying Integration and International Diversification Strategies. *Journal of Empirical Finance*, *16*, 368-387.

Bai, Y., & Green, C. (2010). International diversification strategies: revisited from the risk perspective. *Journal of Banking and Finance, 34*, 236-245.

Basher, S., Nechi, S., & Zhu, H. (2014). Dependence patterns across gulf Arab stock markets: A copula approach. *Journal of Multinational Financial Management*.

Bauwens, L., Hafner, C., & Laurent, S. (2012). Volatility models. In L. Bauwens, C. Hafner, & S. Laurent, *Handbook of volatility models and their applications* (pp. 1-45). New Jersey: Wiley & Sons.

Bauwens, L., Lauren, S., & Rombouts, J. V. (2006). Mutlivariate GARCH models: A survey. *Journal of Applied Econometrics, 21*, 79-109.

Berg, D. (2009). Copula goodness-of-fit testing: an overview and power comparison. *Eur. J. Finance, 15*(7-8), 675–701.

Bhatti, M., & Nguyen, C. (2012). Diversification evidence from international equity markets using extreme values and stochastic copulas. *Journal of International Financial Markets, Institutions & Money, 22*, 622– 646.

Bhatti, M., Al-Shanfari, H., & Hossain, M. (2006). *Econometrics Analysis of Model Testing and Model Selection.* Ashgate Publishing.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31* (1), 307-327.

Bollerslev, T. (1987). A conditional heteroskedastic model for speculative prices and rates of return. *Review of Economics and Statistics, 69*, 542-547.

Boyer, B., Kumagai, T., & Yuan, K. (2006). How do crises spread? Evidence from accessible and inaccessible stock indices. *Journal of Finance, 61*, 957–1003.

Brooks, R., & Del Negro, M. (2003). The Rise in Comovement Across National Stock Markets:Market Integration or IT Bubble? *Journal of Empirical Finance, 11*, 659-680.

Carrieri, F., Errunza, V., & Hogan, K. (2007). Characterizing World Market Integration Through Time. *Journal of Financial and Quantitative Analysis, 42*, 915-940.

Carrieri, F., Errunza, V., & Sarkissian, S. (2004, Working Paper, McGill University). The dynamics of geographic versus sectoral diversification: is there a link to the real economy?

Celik, S. (2012). The more contagion effect on emerging markets: The evidence of DCC-GARCH model. *Economic Modelling, 29,* 1946–1959.

Chen, X., & Fan, Y. (2005). Pseudo-likelihood ratio tests for semiparametric multivariate copula model selection. *Can. J. Statist, 33,* 389–441.

Cherubini, U., Luciano, E., & Vecchiato, W. (2004). *Copula Methods in Finance.* West Sussex, Englad: John Wiley & Sons.

Chiang, T., Jeon, B., & Li, H. (2007). Dynamic correlation analysis of financial contagion: evidence from Asian markets. *Journal of International Money and Finance,* 1026–1228.

Cho, J., & Parhizgari, A. (2008). East Asian financial contagion under DCC-GARCH. *International Journal of Banking and Finance, 6*(1).

Chollete, L., Peña, V. d., & Lu, C.-C. (2011). International diversification: A copula approach. *Journal of Banking & Finance, 35*, 403–417.

Christoffersen, P., Errunza, V., Jacobs, K., & Langlois, H. (2011). Is the Potential for International Diversification Disappearing? *16th Annual Global Investment Conference.* Banff, Alberta.

Corsetti, G., Pericoli, M., & Sbracia, M. (2005). Some contagion, some interdependence:more pitfalls in tests of financial contagion. *Journal of International Money and Finance, 24*, 1177–1199.

Coudert, V., & Gex, M. (2010). Contagion inside the credit default swaps market: The case of the GM and ford crisis in 2005. *Journal of International Financial Markets, Institutions and Money*, *20*(2), 109-134.

Das, S., & Uppal, R. (2004). Systemic risk and international portfolio choice. *Journal of Finance, 59*, 2809-2834.

Delatte, A.-L., & Lopez, C. (2013). Commodity and equity markets: Some stylized facts from a copula approach. *Journal of Banking & Finance, 37*, 5346–5356.

Dungey, M., & Martin, V. (2007). Unravelling financial market linkages during crisis. *Journal of Applied Econometrics, 22*, 89-119.

Embrechts, P., McNeil, A., & Straumann, D. (2001). *Correlation and dependence in risk management: Properties and pitfalls.* Departement Mathematik, ETHZ.

Engle, R. (2002). Dynamic conditional correlation—a simple class of multivariate GARCH models. *Journal of Business and Economic Statistics, 20*, 339-350.

Engle, R., Shephard, N., & Sheppard, K. (2008). *Fitting Vast Dimensional Time-Varying Covariance Models.* (Working Paper, New York University).

Enlge, R., & Kelly, B. (2012). Dynamic Equicorrelation. *Journal of Business & Economic Statistics*, *30*(2).

Erb, C., Harvey, C., & Viskanta, T. (1994). Forecasting international equity correlations. *Financial Analysts Journal*, *50*, 32-45.

Fermanian, J. (2005). Goodness of fit tests for copulas. *Journal of Multivariate Analysis*, *95*, 119–152.

Forbes, K., & Rigobon, R. (2002). No Contagion, Only Interdependence: Measuring Stock Market Comovements. *The Journal of Finance*, 2223-2261.

Garcia, R., & Tsafack, G. (2011). Dependence structure and extreme comovements in international equity and bond markets. *Journal of Banking and Finance, 35*, 1954-1970.

Genest, C., Quessy, J., & Remillard, B. (2006). Goodness of fit test procedures for copula models based on the probability integral transformation. *Scand. J. Statist, 33,* 337–366.

Goetzmann, W., Li, L., & Rouwenhorst, K. G. (2005). Long-Term Global Market Correlations,. *Journal of Business*, *78*, 1-38.

Goetzmann, W., Rouwenhorst, G., & Li, L. (2005). Longer term global market correlations. *Journal of Business, 78*, 1-38.

Hans, M. (2007). *Estimation and model selection of copulas with an application to exchange rate.* Maastricht Research School of Economics of Technology and Organizations.

Hansen, B. (1994). Autoregressive conditional density estimation. *International Economic Review, 35*, 705-730.

Hashmi, A. R., & Tay, A. S. (2012). Mean, Volatility and Skewness Spillovers in Equity Markets. In L. Bauwens, C. Hafner, & S. Laurent, *Handbook of Volatility Models and Their Applications* (pp. 127-145). New Jersey: Wiley & Sons, Inc.

Heinen, A., & Valdesogo, A. (2012). Copula-base volatility models. In L. Bauwens, C. Hafner, & S. Laurent, *Handbook of volatility models and their applications* (pp. 293-316). New Jersey: Wiley & Sons.

Hu, L. (2006). Dependence patterns across financial markets: a mixed copula approach. *Applied Financial Economics, 16*, 717–729.

Huyghebaert, N., & Wang, L. (2010). The co-movement of stock markets in East Asia:Did the 1997–1998 Asian financial crisis really strengthen stock market integration? *China Economic Review, 21*, 98-112.

Ibragimov, R., Jaffee, D., & Walden, J. (2009). Non-diversification traps in catastrophe insurance markets. *Review of Financial Studies, 22*(3), 959-993.

International Monetary Fund. (2014, April). *Regional Economic Outlook: Asia and Pacific.* International Monetary Fund.

Jayasuriya, S. A. (2011). Stock market correlations between China and its emerging market neighbors. *Emerging Markets Review, 12*, 418–431.

Joe, H. (1997). *Multivariate Models and Dependence Concepts.* London: Chapman and Hall.

Joe, H., & Xu, J. (1996). *The estimation method of inference functions for margins for multivariate models.* (Technical Report no. 166, Department of Statistics, University of British Columbia).

Jondeau, E., & Rockinger, M. (2006). The copula-GARCH model of conditional dependencies: An international stock market application. *Journal of International Money and Finance, 25*, 827-853.

Jondeau, E., Poon, S.-H., & Rockinger, M. (2007). *Financial Modeling Under Non-Gaussian Distributions.* London: Springer.

Khan, S., & Park, K. (2009). Contagion in the stock markets: the Asain financial crisis revisited. *Journal of Asian Economics, 20,* 561–569.

Kim, T. H., & White, A. (2004). On more robust estimation of skewness and kurtosis:simulation and application to the S&P500 index. *Finance Research Letters, 1*, 56-70.

King, M., Sentana, E., & Wadhwani, S. (1994). Volatility and Links Between National Stock Markets. *Econometrica, 62*, 901-933.

Kizys, R., & Pierdzioch, C. (2009). Changes in the international comovement of stock returns and asymmetric macroeconomic shocks. *International Financial Markets, Institutions and Money*, *19*, 289-305.

Kodres, L., & Pritsker, M. (2002). A rational expectations model of financial contagion. *Journal of Finance, 57*(2), 768-799.

Li, Q., Yang, J., Hsiao, C., & Chang, Y.-J. (2005). The relationship between stock returns and volatility in international stock markets. *Journal of Empirical Finance, 12,* 650–665.

Longin, F., & Solnik, B. (2001). Extreme correlations in international equity markets. *Journal of Finance, 56*, 649-676.

Missio, S., & Watzka, S. (2011). *Financial Contagion and the European Debt Crisis.* (CESifo Working Paper Series No. 3554).

Nelsen, R. (2006). *An Introduction to Copulas* (2nd ed.). New York: Springer.

Ozdemir, Z. A. (2009). Linkages between international stock markets: A multivariate long-memory approach. *Physica A, 388*, 2461-2468.

Patton, A. (2004). On the out-of-sample importance of skewness and asymmetric dependence for asset allocation. *Journal of Financial Econometrics, 2*, 130-168.

Patton, A. (2006a). Estimation of multivariate models for time series of possibly different lengths. *Journal of Applied Econometrics, 21*, 147-173.

Patton, A. (2006b). Modelling asymmetric exchange rate dependence. *International Economic Review*, *47*(2), 527–556.

Patton, A. (2012). A review of copula models for economic time series. *Journal of Multivariate Analysis*, *110*, 4-18.

Patton, A. (2012). Copula Methods for Forecasting Multivariate Time Series. In G. Elliot, & A. Timmermann, *Handbook of Economic Forecasting* (Vol. II). Oxford: Elsevier.

Peng, Y., & Ng, W. L. (2012). Analysing financial contagion and asymmetric market dependence with volatility indices via copulas. *Ann Finance, 8*, 49-74.

Poon, S.-H., Rockinger, M., & Tawn, J. (2004). Extreme value dependence in financial markets: diagnostics, models, and financial implications. *Review of Financial Studies*, *17*, 581-610.

R, E., & Mezrich, J. (1996). GARCH for Groups. *Risk, 9*, 36-40.

Rahman, H., & Young, K. (1994). Atlantic and Pacific stock markets-Correlation and volatility transmission. *Global Finance Journal, 5*(1), 103-119.

Reboredo, J. C. (2013). Is gold a safe haven or a hedge for the US dollar? Implications for risk management. *Journal of Banking & Finance, 37*, 2665–2676.

Rungcharoenkitkul, P. (2011). *Risk Sharing and Financial Contagion in Asia: An Asset Price Perspective.* (IMF Working Paper WP/11/242).

Samuelson, P. (1967). General proof that diversification pays. *Journal of Financial and Quantitative Analysis*, 1-13.

Schröder, M., & Schüler, M. (2003). *The systemic risk potential in European banking-evidence from bivariate GARCH models.* (Centre for European Economic Research (ZEW), Mannheim).

Shin, H. (2009). Securitisation and system stability. *Economic Journal*, *119*, 309-322.

Sklar, A. (1959). Fonctions de Riépartition á n Dimensions et Leurs Marges. *Publications de l'Institut Statistique de l'Université de Paris, 8*, 229-231.

Syllignakis, M., & Kouretas, G. (2011). Dynamic correlation analysis of financial contagion: Evidence from the. *International Review of Economics and Finance*, 717-732.

Tai, S. (2007). Market integration and contagion : evidence from Asian emerging stock and foreign exchange markets. *Emerging Markets Review*, *8*(4), 264-283.

Tastan, H. (2006). Estimating time-varying conditional correlations between stock and foreign exchange markets. *Physica A*, *360*, 445–458.

Tse, Y., & Tsui, A. (2002). A multivariate GARCH model with time-varying correlations. *Journal of Business and Economic Statistics, 20*, 351-362.

Veldkamp, L., & Van Nieuwerburgh, S. (2010). Information acquisition and under-diversification. *Review of Economic Studies*, *77*(2), 779-805.

Wang, Y.-C., Wu, J.-L., & Lai, Y.-H. (2013). A revisit to the dependence structure between the stock and foreign exchange markets: A dependence-switching copula approach. *Journal of Banking & Finance, 37*(5), 1706-1719.

Wanga, Y.-C., Wua, J.-L., & aic, Y.-H. (2013). A revisit to the dependence structure between the stock and foreign exchange markets: A dependence-switching copula approach. *Journal of Banking & Finance*, 1706-1719.